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Anatomy of the Italian occupational structure: concentrated power and distributed knowledge

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Abstract

Which type of work do Italians perform? In this contribution, we aim at detecting the *anatomy* of the Italian occupational structure by taking stock of a micro-level dataset registering the task content, the execution of procedures, the knowledge embedded in the work itself, called ICP (Indagine Campionaria sulle Professioni), the latter being comparable to the U.S. O*NET dataset. We perform an extensive empirical investigation moving from the micro to the macro level of aggregation. Our results show that the Italian occupational structure is strongly hierarchical, with the locus of power distinct by the locus of knowledge generation. It is also weak in terms of collaborative and worker involvement practices, and possibility to be creative. Our analysis allows to pinpoint the role exerted by hierarchical structures, decision-making autonomy, and knowledge as the most relevant attributes characterizing the division of labor.

JEL classification: J2, D2, C38

1. Introduction

Which type of work do Italians perform? This work aims at detecting the *anatomy* of the Italian occupational structure by taking stock of a unique micro-level dataset—the Indagine Campionaria sulle Professioni (ICP)[1]—providing detailed information on tasks, skills, abilities, knowledge as well as on the technological, organizational, and procedural sequences of the activities done at the workplace. In this respect, the ICP constitutes the only European data source closely replicating the US O*Net repertoire by reporting, for all Italian occupations at the finest degree of disaggregation (i.e. five-digit), a notable amount of data concerning unique characteristics of work.

Departing from the standard approach mainly focusing on individual comparative advantage, in this study we put human agency (Hurley and Fernández-Macías, 2016) and organizations at the center of the stage by intersecting the capability-based theory of the firm, the sociology of work, with particular reference to the labor process theory

1 The ICP is realized by the National Institute for Public Policy Analysis (INAPP) jointly with the Italian National Statistical Institute (ISTAT).

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(Knights and Willmott, 1990, LPT thereafter), and the organizational theory. We intend *work* as the outcome of a process of continuous learning and evolving capabilities, involving tacit and codified knowledge, shaped by the coevolution of hierarchical organizational routines, continuously adapting to procedural uncertainty (Dosi *et al.*, 2001). In so doing, we enlarge both the material-task approach, which interprets work as the process of transformation upon a given object (Hurley and Fernández-Macías, 2016), and the task-based approach (Autor, 2015) which only focuses on the link between purported technological change and substitutability/complementarity with human activity. Therefore, by explicitly considering power relationships and workplace hierarchies as crucially affecting the technology-knowledge-work nexus, our contribution intends to enlarge the domains of analysis currently established in the literature.

We perform an extensive empirical investigation moving from the micro to the macro level of aggregation, with the aim of detecting the dominant traits of the Italian occupational structure. More specifically, the analysis relies on an ex-ante categorization of the dataset focusing on technological, organizational, and skill dimensions namely, *knowledge and learning*; *work organization*, including *degrees of autonomy, routinariety, automation, control, and social interactions*; and finally *ICT skills*. After having identified the variables of interest according to the foregoing domains, we run a factor component analysis to spot the presence of some latent factors. Five common factors allow to explain the variance among our variables, with the factor collecting attributes of *power* explaining most of the variability. Other relevant factors are *cognitive and manual dexterity, ICT knowledge, creativity, and team work*, according to our definitions. Then, we move from the micro four-digit occupations to the macro one-digit ISCO classification in order to understand how the latter factors distribute at different levels of aggregation. Finally, given that Italy stands as the second European country in terms of the share of self-employment,[2] we look at the distinct patterns for employed and self-employed workers in order to check both the robustness of our results and the differences among the two categories.

We find some rather striking results militating in favor of a strongly hierarchical occupational structure, whose locus of power is detached from the one of knowledge generation. In this respect, contrarily to what the "human capital" theory would predict, being endowed by the authority of defining and organizing the division of labor is by far more relevant (to explain inter-occupation variability) than being endowed by high-level knowledge. On the contrary, knowledge attributes are stributed both across factors and occupations. A companion result is that the Italian occupational structure turns out to be weak in terms of team work and collaborative organizational practices. A similar weakness characterizes creative activities and workers' involvement in them. Our conclusions are resilient with respect to the employment status, i.e., no significant difference emerges in the order and magnitude of the factors when splitting the analysis between autonomous and dependent workers, although the two categories present some specificities in the distributional dynamics of the one-digit level occupations.

The paper is organized as follows: in Section 2, we discuss the notion of labor process inside organizations, distinguishing among alternative interpretations, and positioning our own work vis-à-vis the extant literature, in Section 3, we present our dataset, the variables selection and validation, and the empirical analysis carried out. Section 4 replicates the analysis for employed and self-employed workers, while in Section 5, we discuss our findings and limitations, and we conclude, highlighting potential avenues of future research.

2. Different perspectives on labor and organizations

In the following, we shall provide a fresco of some alternative notions of labor deriving from the socio-economic literature. The discussion will allow the reader to get acquainted with the theoretical framework which informed our empirical investigation.

Historically, two main notions of labor can be distinguished. From the one hand, according to Marx, the ownership of the means of production allows to identify the boundary of social classes: labor is defined with respect to its own antinomy with capital and it is the mean of production that needs to be sold to ensure its internal reproduction. Those owning exclusively their physical and mental capacities (i.e. the workers, or "proletariats") will sell their performative counterpart to survive, while those owning the means to exploit and organize labor (i.e. the capitalists) will set the conditions according to which labor activities have to be performed and paid. Labor is the fundamental element out of which *value* is generated by leveraging on workers knowledge and on internal division of power.

2 https://www.eurofound.europa.eu/sites/default/files/ef_publication/field_ef_document/ef1634en.pdf.

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Capitalists are therefore able to appropriate and accumulate the generated value while workers are excluded, and *alienated* from the decision-making process. According to this perspective, the notions of property, class and power are crucial in defining the conceptual borders of labor. From the other hand, the marginalist perspective framed labor as an input of the production function, which might have alternative degrees of substitutability with capital, but whose nature was clearly independent from any power relation vis-à-vis capital. With the marginalist approach, the problem of power relations disappears while the one of optimal allocation becomes dominant: each factor should be rewarded according to its marginal contribution to the production process. As a consequence, elements such as property of the means of production, labor-value, surplus, and class get out of the picture.

The current debate on the impact of automation upon the quantity and the composition of jobs has spurred new attention on the relationship between "human and machines," already there since Ricardo. The dominant discourse has conflated the notion of labor as a *bundle of tasks* which are executed by each worker. Indeed, the nowadays popular task-based approach envisages some limits to the canonical production function framework, regarding its static description of the nature and scope of capital and labor. Consequently, it adopts "job tasks" as unit of analysis, whose supply can derive from domestic, foreign workers or by capital itself, and whose distribution can vary over time, together with the evolution of technologies. The division of tasks between capital and labor ultimately rests upon technological and economic conditions (i.e. labor cost), that jointly determine in a dynamic way the "comparative advantage" between factors, tasks, and skills (Autor, 2013: 5–7). According to such an approach, workers can be defined in terms of the skills required to execute the bundle of tasks they are assigned to and, depending on the degree of repetitive activities performed, they are more or less likely to be substituted by machines. This theory, initially under the heading of skill-bias technical change and later routine-bias technical change (RBTC) has produced a long series of contributions (Autor *et al.*, 2006; Goos *et al.*, 2009, among the others) all trying to document wage polarization via the relationship between the declining price of computers (technology) and the increasing demand for skilled labor.[3] Conceptually, two main critiques have been advanced even by its main proponents: according to Autor and Handel (2013), the relation between tasks (intended as jobs' characteristics) and human capital (intended as workers' individual skills) remains blurred and there might be a significant unaccounted heterogeneity in types and intensity of tasks performed within the same occupation by different workers; on the other hand, social tasks are usually not accounted in this framework, despite they are increasingly demanded as complement to cognitive skills (Deming, 2017). However, these types of criticisms still move within the same theoretical framework, without digging into the nature of work and toward the construction of its actual anatomy. More radical criticisms have come by alternative strands of literature. A comprehensive discussion on pros and cons of the task-based approach is provided in Fernández-Macías *et al.* (2016) who emphasize as limitations the dismissal of the social and institutional reasons behind the technical attribution of tasks in the production process; on a parallel perspective Pfeiffer (2018), focusing on the manufacturing sector, contests the demarcation between cognitive and manual tasks, highlighting the role of knowledge accumulation and subjective experience in the execution of the work activity.

According to our perspective, the task-based approach disregards two main important aspects in defining what people really do at work: first the role of *knowledge* and second the role of *division of labor inside organizations* seen as hierarchical structures wherein knowledge and power are unevenly distributed. In fact, the very nature of the capitalist organization has always involved the power of organizing labor. In this sense, any analysis on the way jobs are performed and more specifically, on how tasks are distributed among occupational roles should not neglect the "socio-economic forces that created them" (Thompson, 1989).[4] One of these forces is explicitly represented by the continuously evolving mechanisms of control over the workforce to ensure the functioning of the production process under specific rules (Edwards, 1980). Historically, this occurred by means of the rationalization of the production process way back since the First Industrial Revolution which entailed a combination of new technological paradigms and organizational innovations. As Adam Smith masterly noticed, the division of labor within organized units dramatically increased productivity, and it did so by transferring knowledge from disorganized artisans and part-time farmers into hierarchical forms of production. In this respect, the process of technological change has entailed a secular deskilling tendency whereby the machine is used to make it codifiable what before was tacit (Nuvolari, 2002).

3 When looking at the quantity of jobs potentially displaced by automation, this stream of research has offered rather different numbers (Arntz *et al.*, 2016; Frey and Osborne, 2017, for two significantly diverging estimates).

4 Thompson (1989: 24) is citing Freedman (1975).

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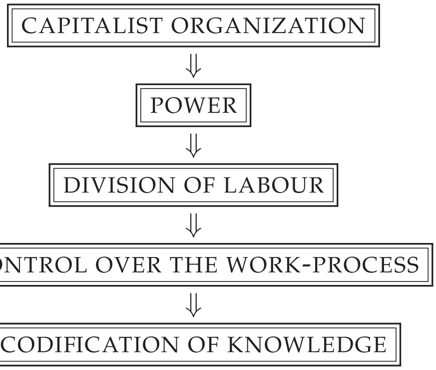

Figure 1. The relation between capitalist organization, knowledge, and power, adapted from Dosi and Virgillito (2019).

Braverman (1974) analyzed such dynamics in contemporary capitalism, detailing the micro-organization of the so called *labor process*: the working class is analyzed in its relationship with the machine, the shop floor, its management, and the related control. The management structure under capitalism is such that the knowledge embodied into workers should be transferred into machines, exerting at the same time a pervasive coordination of all the production units. This ruling class of top- and middle-managers represents the new trait of modern firms (Chandler, 1993: 3) and it is meant to embed its authority into the social structure of the workplace, transforming jobs into a list of titles and descriptions. All this turned into a new form of “bureaucratic control” (Edwards, 1980: 20).[5] Yet, the current organization of work based on skill levels and task types is still perceived as the natural reflection of a technical division of labor into different occupations, neglecting the role played by social and power structures (Thompson, 1989).

What is more, to understand the relationship between human and machines it is crucial to consider technology as an evolutionary process. Think of a technology as a *recipe* with “ingredients,” associated procedures and “admissible acts” required, e.g. to build an artifact. A recipe always embodies a degree of codified knowledge but also noncodified and tacit one (the nonwritten procedures). In turn, the procedures are typically collective implying a process of coordination among members of the organization. The execution of the recipe coordinated among the members of the organization entails an ensemble of *organizational routines*. Organizational routines constitute therefore a *trait d’union* between technology and organization, typically nested into hierarchical structures and power relations (Dosi and Marengo, 2015). Figure 1 illustrates the point. Given the tacit nature of knowledge embodied in the execution of complex tasks, a “natural trajectory” in technical progress has involved the progressive mechanization/automation of production processes and a drive to make simple, repetitive, and codified the routines of the recipe. Control over rhythms and movements along the sequences of production, correct execution of tasks, and discipline of the workforce have been and are the necessary conditions for the codification of knowledge.

Considering the lack of adequate interest in the role played by work organization, related organizational routines, and more generally in the link between power and knowledge inside organizations, we enlarge the domains of analysis and move beyond the notion of work conceived simply as a bundle of tasks to be executed. Therefore, we devote particular attention in framing the labor process inside the organization of production. Crucial elements entail first, the degree of autonomy in performing activities, whereby autonomy captures the extent to which workers have the possibility to set their own rules; second, the degree of control over the production process, which when full even allows the worker to stop the execution of tasks in case of errors; third, degrees of collective knowledge deriving from the existence of learning processes and team working; fourth, degrees of hierarchical power, space of control of the supervisors, space of individual actions and goal setting, and in general the socio-organizational structure (Knights and Willmott, 1990; Dosi and Marengo, 2015). Indeed, a related missing element is the understanding of

5 According to the author, capitalist organizations moved from models of “simple/entrepreneurial control,” directly exerted by the employers at the early stages of industrialization within relatively small companies, to forms of “technical control” and later “bureaucratic control.” Technical control was “embedded in the physical structure of the labour process,” where the introduction of machinery and automation imposed to workers not only strict rhythms of production but also rigid sequences of tasks.

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the firm as the locus of the division and organization of labor. All in all, firms are hierarchical entities wherein knowledge is differently distributed among organizational units and individuals, and the introduction of technological innovation entails processes of uneven learning and adaptation of the different hierarchical layers, in tune with the capability-based theory of the firm (c.f. Winter, 1998; Coriat and Dosi, 1998). If this is so, the types of learning regimes to which workers are solicited, e.g., the degree of updating their own knowledge, the degree of attention they should devote in executing their own work, the possibility to think creatively and to cumulate experience crucially affect the labor process in itself. Finally, complementary elements of our analysis vis-à-vis the task-based approach are the degrees of execution of repetitive tasks and automation/digitalization, such as the use of ICT tools at work, also in line with the PIAAC classification. In the empirical analysis which follows, we explicitly intend to fill the existing gap in the literature by identifying the role of the above-mentioned dimensions in shaping the Italian occupational structure.

3. Empirical analysis

3.1 Data

The anatomy of the Italian occupational structure is dissected by means of the ICP—*Indagine Campionaria delle Professioni*—conducted by the National Institute for Public Policy Analysis (INAPP) in collaboration with the Italian National Statistical Institute (ISTAT). This survey represents the only European source comparable with the American O*Net repertoire (Gallo and Lorè, 2006), being the latter the most comprehensive database reporting qualitative-quantitative information on tasks, skills, work contexts, and organizational characteristics at the five-digit level of observation. The construction of the dataset entails a complex, multi-layer strategy of data collection and information processing allowing for both detailed occupational descriptions and inter-occupation comparability (Peterson *et al.*, 2001).

Currently, two waves of the ICP database are available (2007, 2012) with a spectrum covering 797 occupational codes, excluding armed forces.[6] The interviews are administered to 16 000 Italian workers to ensure statistical representativeness with respect to sectoral, occupational, dimensional, and geographical heterogeneities. The sampling strategy is articulated as follows. Relying on a matrix—built using the Italian Labour Force Survey (LFS) realized by ISTAT—providing information on the distribution of occupations (in terms of number of employees) across five-digit sectors, 797 independent samples are generated. Each sample refers to a specific five-digit occupation and is populated by firms (stratified by region and size class) belonging to the cluster of sectors where the probability of finding such an occupation is above an ex-ante threshold. Firms are randomly extracted from the ISTAT company-level register. The ICP information is then collected according to a two-step procedure. At a first step, firms are contacted by phone to verify the presence of a specific occupational category at five-digit level. Granted the latter, on average, 20 workers per each occupation are interviewed by means of 1-h lasting CAPI (computer-assisted personal interview).

Both O*NET and ICP questions are organized in six main sections, expressions of a content model that simultaneously provides information from a job-oriented and worker-oriented perspective.[7] The descriptors are: *worker characteristics* (enduring abilities and work style of workers), *worker requirements* (skills and education), *occupational requirements* (organizational and work context), *experience requirements* (training, cross-functional skills), *workforce characteristics* (labor market information), and *occupation-specific information* (generalized activities and work context).[8] In so doing, descriptors are formulated by making it possible to distinguish, for instance, inner individual abilities from competences acquired on the job. For each question, two rating scales are generally provided: level and importance. In our analysis, we will pick the level scale only, since it ensures a complete coverage and direct comparability among variables.

6 The following analysis is conducted at four-digit level, considered this level of granularity to be sufficiently appropriate to identify actual job profiles and matchable with other datasets providing additional economic and demographic variables (Gualtieri *et al.*, 2018).

7 For a brief overview on the content model adopted by O*NET consult directly the O*NET website at https://www.onetcenter.org/content.html.

8 Despite the similarities, a significant difference between the ICP and the O*NET databases concerns the set of respondents. In the Italian survey, the information is drawn exclusively from job incumbents—each one compiling the entire questionnaire—while in the American O*NET, different job incumbents do answer to diverse sections for the same occupation, and job analysts are also asked to express opinions on the reported tasks.

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3.2 Variables selection and theoretical validation

The empirical stage consists in the factor analysis of 25 ICP variables, gathered in three main domains of analysis: knowledge and learning, work organization and ICT skills, as presented in Table 1.

1. *Knowledge and learning*. This set of questions collects all variables providing information on both general and specific degrees of knowledge necessary to perform the job. In particular, the questions instruct about the importance of e.g., updating knowledge, needs of using critical thinking, and production of new ideas. These questions allow to dig inside the actual degree of learning processes involving the worker, distinguishing by types of occupations. The theoretical foundation of this group stems from the evolutionary perspective on the role of learning within organizations (Arrow, 1971; Dosi *et al.*, 2001; Stiglitz and Greenwald, 2014).
2. *Work organization*. This set of questions collects information on the forms of work organization that can be elicited from interviews. In fact, in order to characterize what actually people do at work, it is necessary to understand e.g., the degree of autonomy in performing specific tasks and in decision-making, the possibility of solving complex problems, the control over the process, the control and influence on other people, the degree of automation, and repetitiveness of the performed task. In this respect, this set allows to infer information upon the hierarchical position of workers inside organizations. The theoretical references are multiple, coming from Lorenz and Valeyre (2005), Fernández-Macías (2012), and Dosi and Marengo (2015).
3. *ICT skills*. This set of questions allows to gather information on the level of ICT skills required by each occupation, where ICT skills are mainly constructed allowing the distinction between basic users and more advanced ones, in line with the DESI approach followed by the European Commission.[9] Indeed, ICT technologies represent a tool affecting not only the way and the type of tasks performed, but also jobs quality (Rubery and Grimshaw, 2001), workers' autonomy (Mazmanian *et al.*, 2013), and the entire organization structure (Orlikowski, 2000). For this reason, it is important to account for different degrees of intensity in technology usage, from e-mail correspondence to more advanced knowledge of ICT.

The procedure of variables selection has followed several steps. The first step consisted in a qualitative scrutiny of the 400 questions of the ICP. Among the full list of questions, we initially focused on a subset of almost 100 questions covering the three main domains defined above. The subsequent step was to eliminate uninformative questions for our purposes (i.e. knowledge of Italian/foreign language); more complex topics (i.e. types of innovation occurred in each occupation) which may need a separate analysis; questions based on different scales (years of tenure or weekly working hours rather than the level of importance) and those that were already well represented in the subset (training others, monitoring, etc.). This second-round scrutiny resulted into a final set of 70 questions, grouped into the three main domains and related sub-indicators in the case of Work Organization, where we distinguish for Autonomy, Routinariety, Control, and Socio-organizational structure. The set of 70 variables is presented in Table A2 in the Appendix.

Being the ICP an extremely rich and detailed source of data on occupations, several questions might present a high degree of similarity. Therefore, a careful preliminary analysis on the 70 questions has been necessary in order to clean our dataset from superfluous repetitions and over specifications. After performing a descriptive and statistical analysis (mean, standard deviation, pairwise correlation) for each sub-indicator, we excluded similar variables showing a very strong correlation (equal or higher than 0.9) since we assumed they were capturing the same object.[10]

9 https://ec.europa.eu/digital-single-market/en/news/new-comprehensive-digital-skills-indicator.

10 Take the case of the variables "Quality evaluation" and "Evaluation of conformity to standards" or alternatively "Planning the work" and "Organizing priorities": those variables display very high degree of correlation, driving us to select only one of the two. Nonetheless, similar questions may present relevant differences. In that case, we opted for the variable providing neater information. For instance, the two variables "Team-work importance" and "Coordinating with others" show a high level of correlation (0.83), but we identified some ambiguity in the text of the former question, where interacting with others and being part of a team are put on the same level (Table A2). For this reason, we selected "Coordinating with others" as a cleaner proxy of team work and, more generally, of coordination with other workers. Analogously, the variables "Guiding others" and "Leadership" present a high level of correlation (over 0.8), even if they are capturing two different traits of control over people. Indeed, the capability of being leader does not consist only in guiding others but also in persuading them, getting their support and obedience. For this reason, we selected "Leadership."

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Table 1. Domains, variables, and related questions

Domain	Variable	Question
Knowledge and Learning	Update and Use	*Keep up to date with technical changes and apply new knowledge.*
	Creative Thinking	*Develop, design, or create new applications, ideas, relationships and new systems, and products (including artistic contributions).*
	Active Learning	*Understand the implications of new information for the solution of present and future problems and for decision-making processes.*
	Selective Attention	*Ability to focus on a task for a long time without distraction.*
	Distributive Attention	*Ability to follow two or more different activities or sources of information at the same time.*
ICT skills		
	PC Use	*Use computers and computer systems (software and hardware) to program, write software, adjust functions, enter data, or process information.*
	Mail Use	*How often does your profession require the use of e-mail?*
	ICT Knowledge	*Computer science and electronic knowledge.*
Work Organization		
Autonomy in decision	Goal Strategies	*Establish long-term objectives and specify strategies and actions to achieve them.*
	Evaluating and Deciding	*Evaluate the costs and benefits of possible actions to choose the most appropriate.*
Autonomy in planning	Organizing Priorities	*Set specific objectives and plan the work defining priorities, organization, and timing of implementation.*
Autonomy in doing the job	Tool Selection	*Identify the tools needed to do a job.*
	Solving Problems	*Determine the causes of operating errors and decide what to do to solve them.*
	Solving Complex Problems	*Identify complex problems and collect information to evaluate possible options and find solutions.*
Routinariety and automation	Hand Dexterity	*Ability to quickly move hand, hand and arm together or both hands to grab, manipulate, or assemble objects.*
	Automation Degree	*How automated is your work (linked to automatic processes)?*
	Repetitive Movements	*In your work how long do you perform repetitive movements?*
Control over people	Influence	*How often do your decisions affect other people or your employer's image or reputation or financial resources in your work and what impact do they usually have? (average of two questions)*
	Leadership	*The work requires the willingness to guide people, to take charge and to give opinions and directives.*
Control over the process	Inspecting	*Inspect equipment, structures, or materials for causes of error, or other problems or defects.*
	Standard Evaluation	*Use relevant information and individual opinions to determine whether events or processes comply with standards, laws, or regulations.*
	Machine Control	*How important is it in your work to keep sequences of machinery and equipment under control?*
Socio-organizational structure	Relations	*Create constructive and cooperative working relationships and maintain them over time.*
	Coordinating with others	*Coordinate their actions with those of others.*
	Competition	*How competitive is your job (requires constant comparison with the performance of colleagues/other workers)?*

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Moreover, we excluded those variables showing a very low degree of variation across occupational groups, signaling in this case a variable strictly related to a specific set of occupations[11] or rather, a bias or misunderstanding of the exact content of the question.[12]

Table 2 compares some of our adopted variables (first column) vis-à-vis those adopted by the extant literature, therefore external validating our choices but also highlighting the specificities. We distinguish between the task-based approach (second column) and other relevant socio-economic strands (third column). Indeed, some of the chosen variables are frequently used by the former literature, such as "Control over the process" and "Controlling machines" adopted to capture manual routine activities, the variables "Leadership" and "Creative thinking" usually used to capture nonroutine cognitive interpersonal tasks, and the variable "Coordinating with" capturing social interactions (Spitz-Oener, 2006; Acemoglu and Autor, 2011; Autor and Handel, 2013; Deming, 2017).

Vis-à-vis the task-based approach, this study enlarges the spheres of the covered domains by including variables intended to capture elements of the organizational models behind, which might range from more Tayloristic toward more "lean-smart-agile" ones, and of the ensuing learning systems (Arundel *et al.*, 2007; Lundvall and Lorenz, 2012). In fact, different organizational models might influence the degree of workers intervention authority in the process. Therefore, we adopt variables instructing about the possibility of "Solving complex problems," showing the degree of "Active learning" and "Distributed attention," and finally the presence of "Team-working," in line with Lorenz and Valeyre (2005). Overcoming the strict, and somewhat poor, dichotomy between "routine" and "non-routine" work, we want to know the role played by learning by-doing and cumulated experience which allow to act under conditions of uncertainty and possibly to react to unpredictable events (Pfeiffer and Suphan, 2015), being the latter rather desirable abilities even in automatized manufacturing processes usually considered to be routinized. The learning processes and the organizational practices shaping them clearly map into the degree of "Autonomy" of the workers in performing their activity (Vidal, 2013; Cirillo *et al.*, 2020), influencing the space of action in terms of decision-making, e.g. in "Planning your own work" and in "Setting and establishing the time-path" (Harley, 1999). But, to genuinely account for the degree of autonomy one needs to explicitly consider the diffusion and concentration of power in the decision-making process, which can be manifested both in terms of "Leadership" and "Influence" over the others.[13] Notably, although the two latter variables might be considered as specific of the managerial activity only, we deem interestingly to examine the diffusion of these abilities across the entire range of occupations for two reasons: first of all, forms of power are exerted at all levels of the hierarchical structure of organizations[14] and range from explicit disciplinary scopes toward more blurred and implicit ones (e.g. limitation of the space of action, definition of the border of the admissible acts, Thompson and McHugh, 1995), and second, after 30 years of managerial and organizational push toward HPWPs (high-performance work practices), empowerment of the workforce, and lean systems (Piore and Sabel, 1986; Womack *et al.*, 1990; Huselid, 1995), we expect some degree of power to be distributed along the entire layers of the organizational architecture, and internal hierarchies to be less stiffen. Lastly, variables belonging to the domain of ICT skills are intended to describe the extent to which ICT technologies are adopted in the workplace and whether they complement specific attributes of work organization and knowledge. Indeed, we inserted three different questions in order to distinguish intensities in the adoption of technologies, from the simple use of e-mail correspondence, to a more integrated adoption of the computer at work, to the necessity of acquiring and update professional knowledge in computer science and electronics.

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11 For instance, "Programming skills" intensity exhibits very low values across all occupations. The only two groups showing a high intensity are intellectual and scientific workers, and technicians and professionals, confirming its nature of occupation-specific characteristic.

12 A useful example for this purpose is the two variables "Attention to detail" and "Being always busy": since they both show very high and similar values across all occupational groups, this might suggest a potential subjective bias when answering to questions evaluating individual effort and accuracy in performing its own job.

13 "Influence" is the only variable in our dataset constructed as the average of two variables.

14 Take the case of the team-leader or the head of unit which in many cases *do not present* different contractual frameworks but have the ability to exert a ruling role.

Table 2. Variables and theoretical validation

Variables	Task-based approach	Other approaches (Eurofound, LPT, Human Capacity Index)
Creative Thinking	"Thinking Creatively" in Nonroutine cognitive analytical (Acemoglu and Autor, 2011)	
Active Learning		"Learning new things" (Lorenz and Valeyre, 2005)
Distributed Attention		"How often does it happen (...) that you have to keep an eye on different work processes or sequences at the same time?" in situation of specific unpredictability (Pfeiffer and Suphan, 2015)
Goal Strategies	"Direction, Control and Planning" in Nonroutine interactive (Autor *et al.*, 2003)	"Autonomy in decision-making" (Harley, 1999)
Evaluating and Deciding	"Evaluating and planning" in Nonroutine analytical (Spitz-Oener, 2006)	"How often does it happen (...) that you have to take difficult decisions autonomously?" (Pfeiffer and Suphan, 2015)
Organizing priorities	"Direction, control and planning" in Nonroutine interactive (Autor *et al.*, 2003)	"Autonomy in the pace or rate at which work is carried out" (Lorenz and Valeyre, 2005); "Autonomy in how work is done, beginning and ending time" (Harley, 1999)
Solving Complex Problems	"Frequency of problem solving tasks requiring at least 30 minutes to find a good solution" in Abstract (Autor and Handel, 2013)	"Solving problems" (Lorenz and Valeyre, 2005); "How often does it happen (...) that you have to react to and solve problems?"(Pfeiffer and Suphan, 2015)
Hand Dexterity	"Finger Dexterity" in Routine manual (Autor *et al.*, 2003); "Manual Dexterity" in Nonroutine manual physical (Acemoglu and Autor, 2011)	
Automation Degree	"How automated is the job?" in Routine task intensity (Deming, 2017); "Pace determined by speed of equipment" in Routine manual (Acemoglu and Autor, 2011)	"Automatic constraints linked to the rate at which equipments are operated or a product is displaced in the production flow" (Lorenz and Valeyre, 2005)
Repetitive Movements	"Spending time making repetitive motions" in Routine manual (Acemoglu and Autor, 2011)	"Monotony" and "Repetitiveness of tasks of less than one minute" (Lorenz and Valeyre, 2005)
Influence		"Hierarchical constraints linked to the direct control exercised by one's immediate superiors" (Lorenz and Valeyre, 2005)
Leadership	"Guiding, directing and motivating subordinates" in Nonroutine cognitive interpersonal (Acemoglu and Autor, 2011); "Managing Personnel" in Nonroutine interactive (Spitz-Oener, 2006); "Proportion of workday managing or supervising other workers" in Abstract (Autor and Handel, 2013)	Hierarchy intended as occupational groups (Harley, 1999)
Standard Evaluation	"Set limits, tolerance and standard" in Routine cognitive (Autor *et al.*, 2003)	"Quality assessment" (Lorenz and Valeyre, 2005)
Machine Control Importance	"Controlling machines and processes" in Routine manual (Acemoglu and Autor, 2011), "Operating and controlling machines" in Routine cognitive (Spitz-Oener, 2006)	
Relations	"Establishing and maintaining personal relationships" in Nonroutine cognitive interpersonal (Acemoglu and Autor, 2011); "Social perceptiveness" in Social skills (Deming, 2017)	
Coordinating with others	"Coordination" in Social skills (Deming, 2017)	"Team-work"/"Horizontal constraints linked to the dependence on the work of colleagues" (Lorenz and Valeyre, 2005)

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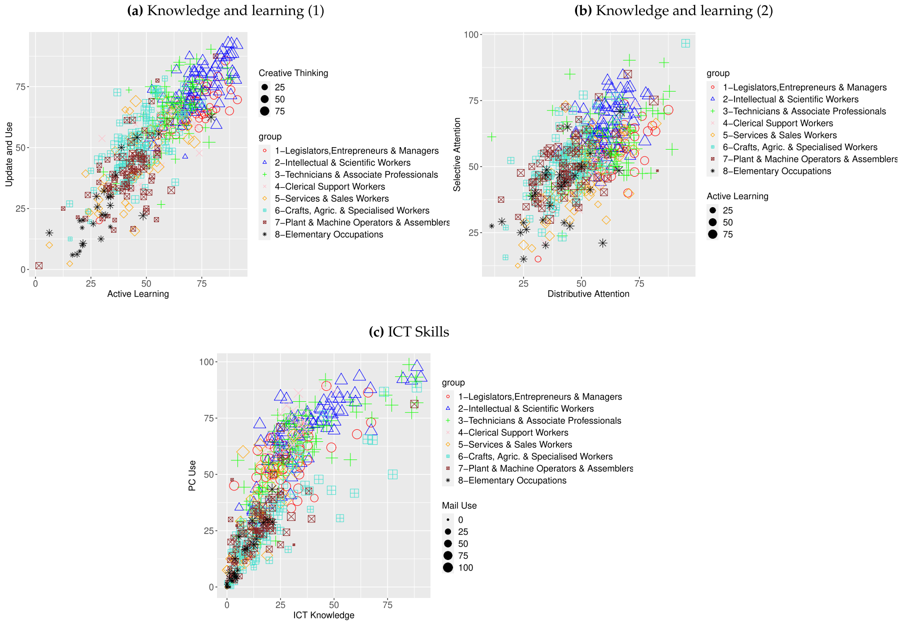

Figure 2. Knowledge and ICT variables across four-digit occupations—three-variate correlations. (a) Knowledge and learning (1), (b) Knowledge and learning (2), and (c) ICT Skills.

3.3 Descriptive statistics

Do the foregoing domains present an empirical consistency? We start with a set of descriptive statistics. While Figure A1 in the Appendix presents the average value of variables by one-digit occupation grouped in domains and sub-domains,[15] here we look at the three-variate cross-correlation among variables by each domain (or corresponding sub-domain in the case of work organization) distinguishing by four-digit occupations (different colors and shapes). Both knowledge and learning, ICT skills (Figure 2) and work organization (Figure 3) are characterized by variables with positive cross-correlation, empirically validating the internal consistency of domains. However, a varying degree of heterogeneity within the main occupational groups can be envisaged. Looking for instance at intellectual and scientific workers (blue triangles), for "knowledge and learning" (Figure 2a) the group explicitly defines a "cluster" in the upper part of the graph, while for other sub-domains like "autonomy in planning" and "autonomy in doing the job" (Figure 3a and b), the group shows a more dispersed pattern, recording both high and low values. The same behavior characterizes other occupational groups and variables, as in the case of "routinariety and automation" (Figure 3c) where almost all ISCO classes at four-digit (apart for the first two) are scattered, showing strong internal heterogeneity in terms of levels of "hand dexterity," "repetitive movements," and "automation degree." The exception to this dispersed behavior is the sub-domain "control over people" wherein a clear increasing pattern from low-end to top-end ISCO groups emerges (Figure 3d).

We next focus on the kernel density distributions across ISCO groups of a selected set of variables considered to be informative for the following analysis. For what concerns ICT knowledge (Figure 4a), we observe a very scarce diffusion of this competence across all occupational groups, even among technicians and intellectual workers where only a small fraction of occupations—corresponding to few ICT-specialized jobs—exhibits high levels of computer science knowledge. Nevertheless, intellectual and scientific workers are also the ones recording a more significant need of continuous learning as shown by the densities of "update and use of new knowledge" (Figure 4b). At the

15 The one-digit level aggregation results into eight occupational categories namely: legislators, entrepreneurs, managers; intellectual and scientific workers; technicians and associate professionals; clerical support workers; service and sale workers; crafts, agriculture and specialized workers; plant and machine operators and assemblers; elementary occupations. See Table A1 for reference.

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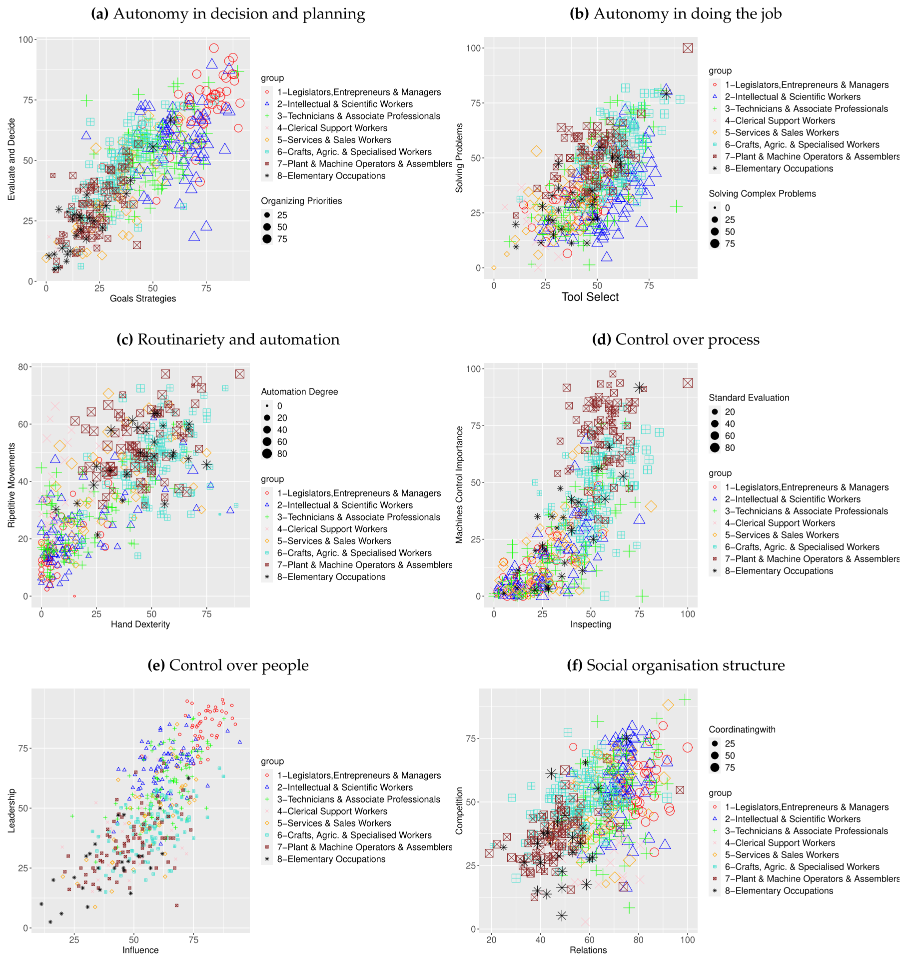

Figure 3. Work organization variables across four-digit occupations—three-variate correlations. (a) Autonomy in decision and planning, (b) Autonomy in doing the job, (c) Routinariety and automation, (d) Control over process, (e) Control over people, and (f) Social organization structure.

opposite, legislators, entrepreneurs, and managers exhibit a normal density centered on a lower level of intensity assigned to the need of being updated with technical changes and innovations.

"Solving problems" (Figure 4c), intended as solving unexpected malfunctions and process breakdowns, looks to be essentially an attribute of crafts, agricultural workers, plant-machine operators, and partly of clerical workers. This evidence confirms that even those occupations showing a relevant degree of repetitive movements (Figure 3d) are supposed to perform their tasks in a dynamic and flexible way in order to promptly deal with unexpected problems that can occur with a certain frequency. This necessity, however, conflicts with the much lower level of autonomy in decision-making recorded by these workers, as shown by the distribution of "evaluating and deciding" (Figure 4e), where the highest values are almost exclusively reported within the first ISCO class of legislators, entrepreneurs, and managers that, in turn, are also the ones with the highest scores in terms of capability of influencing and orienting people decisions (Figure 4f).

This deep heterogeneity across domains and occupations confirms the importance of intertwining a double level of analysis, combining different degrees of aggregation in order to both appreciate four-digit occupational specificities and identify the main common attributes of one-digit occupational groups. How does the entire set of variables distribute across the Italian occupational structure? What kind of relations is possible to detect among variables belonging to different domains? The goal of the empirical analysis will be exactly to understand the emergence of

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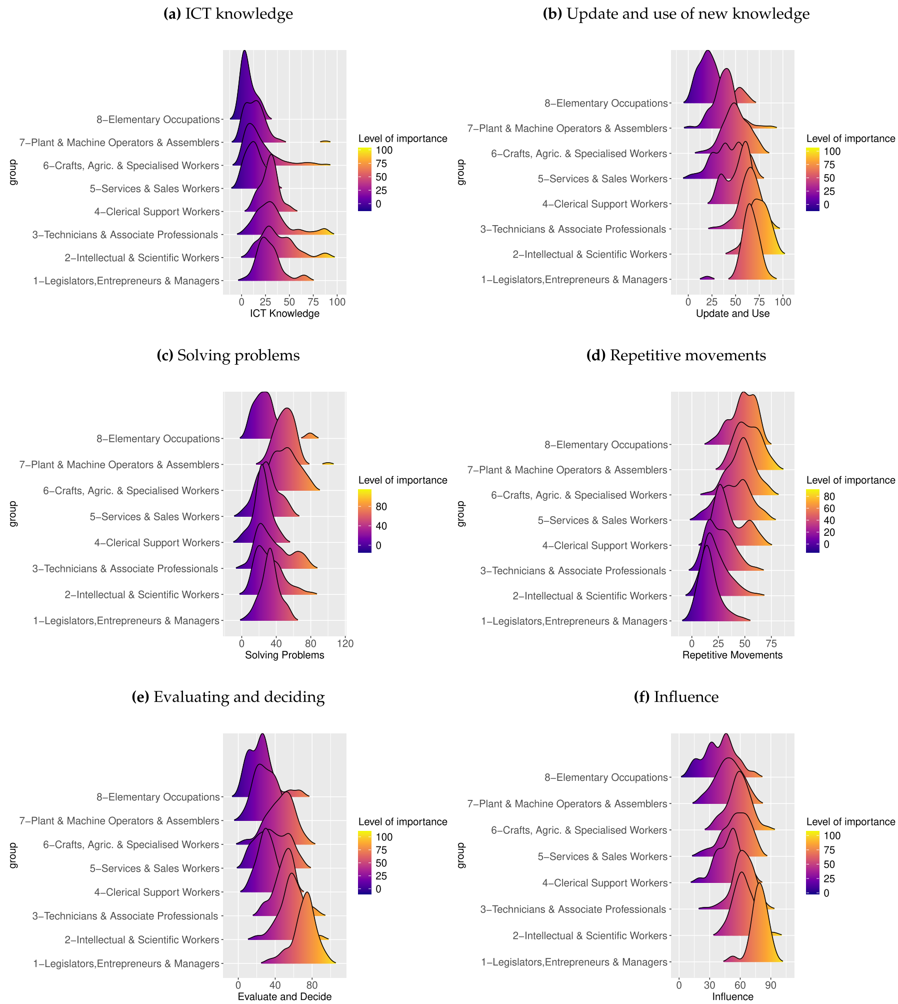

Figure 4. Selected variables— kernel density distributions across ISCO groups. (a) ICT knowledge, (b) Update and use of new knowledge, (c) Solving problems, (d) Repetitive movements, (e) Evaluating and deciding, and (f) Influence.

hidden factors able to explain cross-correlations among variables, similarities, and differences within and between the main occupational groups.

3.4 Factor analysis

Given the unique richness of information contained in this type of data, different empirical analyses can be potentially implemented. In fact, the O*NET has already been used to build the Routine task index (Autor, 2015), on the application of which an important stream of literature on job polarization originates. Furthermore, the American survey O*NET has been screened adopting different methodologies—as the factor analysis—in order to deepen the knowledge on occupational characteristics, providing a taxonomy of skills and industry capabilities (Consoli and Rentocchini, 2015) or detecting the emergence of "green jobs" (Consoli *et al.*, 2016). In our case, the choice of the factor analysis, which allows to identify constructs accounting for the correlation between variables (Kline, 2014), is motivated by the aim of grasping the most relevant underlying factors characterizing the anatomy of the Italian occupational structure. In fact, taxonomies allow to identify characteristic traits of a given dataset and to search for differences and similarities with respect to its internal categories (Peneder, 2010). To the best of our knowledge, this is the first time a similar empirical study is presented using the ICP database.

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In matrix form, the statistical model underlying the factor analysis reads as[16]:

$$Y = \Lambda X + \Psi E, \tag{1}$$

where Y is a (nx1) vector of random variables, X is a (rx1) vector of common factors, and E is a (nx1) vector of unique factors, with $n > r$; Λ is a (nxr) matrix of common factor coefficients and Ψ is a (nxn) diagonal matrix of unique factor coefficients. According to equation (1), the vector Y is therefore a weighted combination of common and unique factors. Λ and Ψ contain, respectively, the weights of the common and unique factors, where the former is populated by non-zero common weights attributed to each factor per variable, while the latter consists of a diagonal of unique non-zero weights per each variable. Common and unique factors are assumed to be uncorrelated. The goal of the factor analysis is to identify common factors able to account for linear combinations among the variables under study, distinguishing source of common variance from unique variance, which can depend both on random errors or specific variance of each variable.

Assuming $R_{XE} = R'_{EX} = 0$, from equation (1), we derive:

$$E(YY') = R_{YY} = E(\Lambda X + \Psi E)(\Lambda X + \Psi E)' = \Lambda R_{XX} \Lambda' + \Psi^2. \tag{2}$$

Equation (2) is the fundamental theorem of factor analysis, from which the reduced correlation matrix R_c is derived. The latter is obtained by subtracting from the variance-covariance matrix of Y the matrix of unique factors:

$$R_c = R_{YY} - \Psi^2 = \Lambda R_{XX} \Lambda'. \tag{3}$$

Since Ψ is a diagonal matrix, the off-diagonal coefficients of R_c will preserve the variables' commonalities, that are correlations due to common factors only. Λ will be the focus of our empirical analysis as it represents the factor pattern matrix, whose coefficients correspond to the weights attributed to the common factors, once derived the variables of the sample as linear combinations of common and unique factors. Indeed, Λ can also be defined as follows:

$$\Lambda = R_{YX} R_{XX}, \tag{4}$$

where R_{YX} is the factor structure matrix whose coefficients correspond to the covariances between variables Y and factors X, and R_{XX} is the correlation matrix between factors. Under the hypothesis of factors orthogonality Λ and R_{YX} are equivalent (being $R_{XX} = I$). However, as we shall see, the assumption of orthogonality among factors looks inappropriate for our study.

Different preliminary tests have been run in order to check the factorability of the database, whose sample size of 507 observations can be considered strongly reliable (Comrey and Lee, 1992). First of all, a preliminary analysis on the correlation matrix among the 25 selected variables has been performed to check the presence of an adequate correlation structure. The correlation matrix, shown in Figure 5, presents the emergence of three "clusters" of variables: from the left-hand side to the right-hand side, the blue area shows the emergence of positive correlation (from "being creative" up to "coordinating with others"), the white area of low correlation (from "tool selection" up to "inspection"), while the red area of negative correlation (from "repetitive movements" up to "control machine importance") among variables.

In order to understand whether the selected dataset presents the characteristics to be factorized, we performed the Kaiser–Meyer–Olkin test that delivers a value of 0.92, confirming data adequacy. The latter indicator consists in the ratio of the sum of squared correlations over the sum of squared correlations plus the sum of squared partial correlations (Tabachnick et al., 2007: 614): the closer to 1, the lower is the value of partial correlations, and therefore, the higher the adequacy of the sample. Moreover, we run the Fligner nonparametric test that assesses variance homogeneity similarly to the Bartlett sphericity test, the former being more robust to departure from normality than the latter. The test rejects the null hypothesis on the equality of the distributions (and on the assumption of an identity correlation matrix). Additionally, the Alpha Cronbach test confirms the internal consistency of the set of chosen variables.

Once ascertained data factorability, the number of factors has been chosen taking into account different criteria: parallel analysis, factors' variance explained, and Kaiser's criterion (eigenvalue > 1) which are alternative and reliable selection methods to retain only the significant eigenvalues. The parallel analysis, presented in Figure 6, indicates the

16 In the following paragraph, we follow the theoretical explanation provided by Mulaik (2009).

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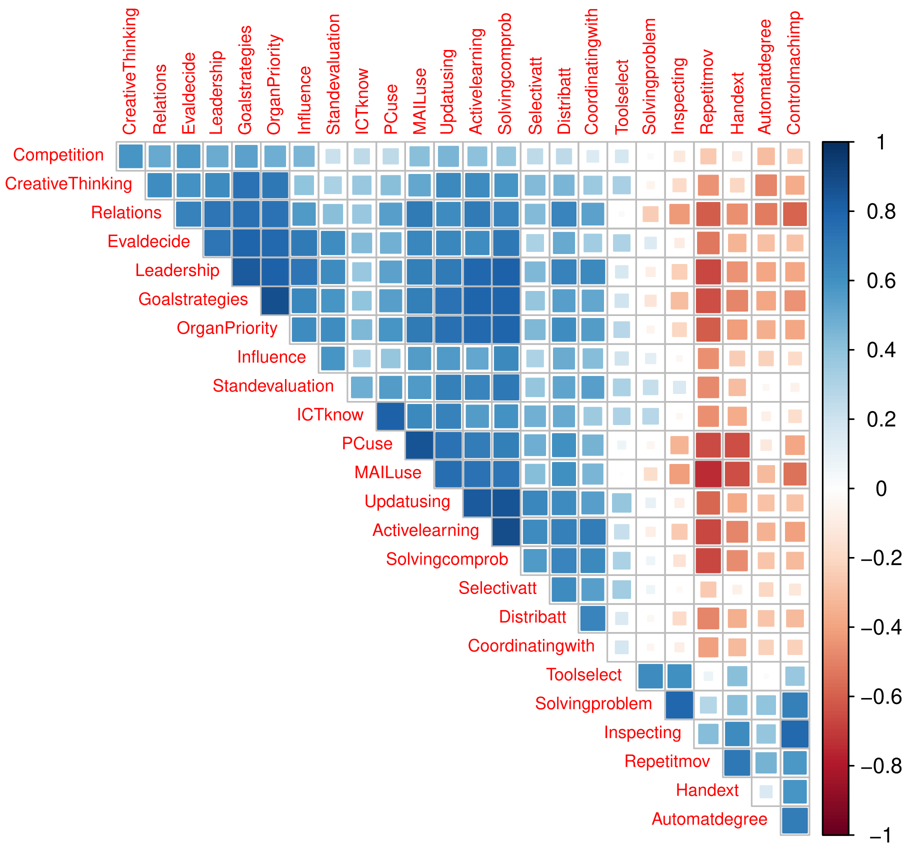

Figure 5. Correlation matrix.

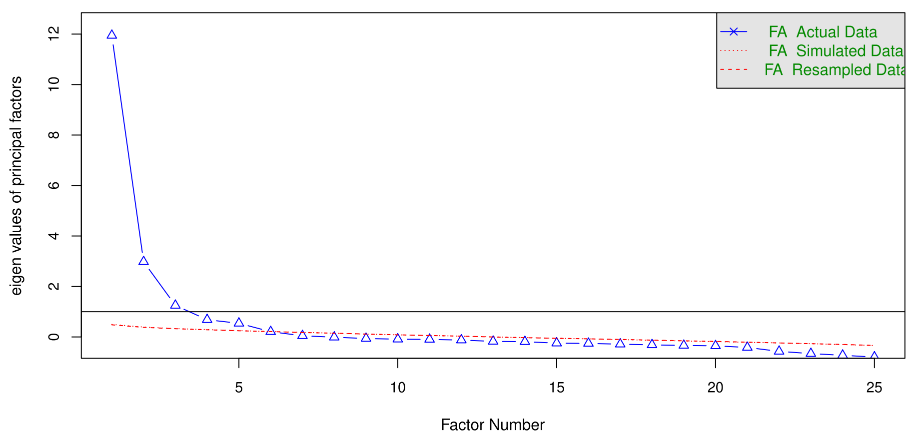

Figure 6. Parallel analysis scree plot.

significant number of eigenvalues to select by comparing the actual matrix with a simulated and re-sampled random matrix with the same characteristics of the original matrix. The blue line indicates eigenvalues from actual data, whereas the two (overlapping) red lines report simulated and re-sampled data. In this case, we identify the number of factors to retain whereby the distance between the blue and red lines is minimum: the selected number of factors

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equals five. This outcome is supported both by the compliance with the Kaiser criterion and the satisfactory amount of variance explained by the five factors.[17]

Different extraction methods have been adopted (principal axis, minimum residuals, weighted and unweighted least squares), all delivering very similar outcomes. In the following figures, we display the outcomes of the principal axis analysis that is based on an iterative algorithm computing eigenvalues and eigenvectors of the characteristic equation in order to obtain, at the end of the process, the most representative factors able to account for the maximum amount of variance.[18]

In order to improve results' interpretability, the Promax rotation has been applied. Indeed, we opted for oblique rotation that allows the possibility of correlation among factors since we assume that, as usual in social science (Tabachnick et al., 2007), factors explaining occupational characteristics might present correlation. In fact, we found out the presence of significant correlation among four out of five factors. Furthermore, factor scores have been calculated with different methods without delivering significant differences but, for the sake of simplicity, only regression's scores are reported.

3.5 Results

Figure 7 shows the results of the factor analysis. The circles represent the five factors in descending order of relative importance, while the arrows departing by each circle connect the loaded variables, black and red for positive and negative loadings, respectively. The numbers indicate the respective loads. Complementary, Table 3 displays the pattern matrix that in the case of oblique rotation can be opportunely interpreted as variable loadings (Tabachnick et al., 2007). The five factors explain more than 70% of the variance of the dataset, with the first three contributing the most. Finally, the arrows linking circles represent the degree of between-factors correlation, which ranging from 0.4 up to 0.7 is not negligible and calls for the Promax rotation method, removing the hypothesis of factor orthogonality.

The first factor predominantly collects those variables belonging to the domains of *autonomy (in decision, planning, and doing the job)* and *control over other people*, cf. Table 1. As can been seen from Table 3, the loads of the variables are approximately in the range of 0.9–0.5. Notably, those variables related to routinariety indicators, as the frequency of repetitive movements and hand dexterity, negatively load. By loading all variables related to the domains of autonomy and control, we deem appropriate to label this factor *Power*. The choice is driven by the fact that this factor describes behaviors and attributes typical of the expression of forms of power, intended as:

> the ability of some agent (the 'ruler', the authority) to determine the set of actions available to the other agents (the 'ruled') [or even] the ability of the authority to influence or command the choice within the 'allowed' choice set. (Dosi and Marengo, 2015: 538)

This factor explains one-fourth of the total variance and the loaded variables represent the predominant traits in determining four-digit inter-occupational variation. Clearly, activities as establishing long-term objectives and specifying strategies, and actions to achieve them, or setting specific objectives and planning the work, or defining priorities, organization and timing of implementation, are typically performed by the upper hierarchical layers inside organizations. In this respect, the sheer finding that the most important factor in determining cross-occupational variation is linked with hierarchies signals how catching what actually people do at work dramatically depends on the internal distribution of power. Note, however, that the variables loading in the *Power* factor are not only those explicitly signaling hierarchical control, such-as "Leadership," but also variables referring to forms of more general "Autonomy" in judgment and decision-making, which affect, with different degrees, the entire range of occupational categories.

The second most important factor which explains an additional 15% of variability across four-digit occupations collects six variables related to the execution of cognitive activities manifested as forms of control over the process, e.g., selecting machine tools or inspecting equipments, and by the execution of tasks which present a high degree of repetitive and automated motions and involve manual dexterity. We labeled this factor *Cognitive and manual dexterity*. Differently from our ex-ante classification (cf. Table 1), this factor loads positively both activities related to the

17 The last factor shows an eigenvalue only slightly higher than 1, however, given the result of the parallel analysis, the amount of variance explained and the factor interpretability we are confident in keeping it in our model.

18 For further details on the psych package on R, see http://personality-project.org/r/psych/HowTo/factor.pdf.

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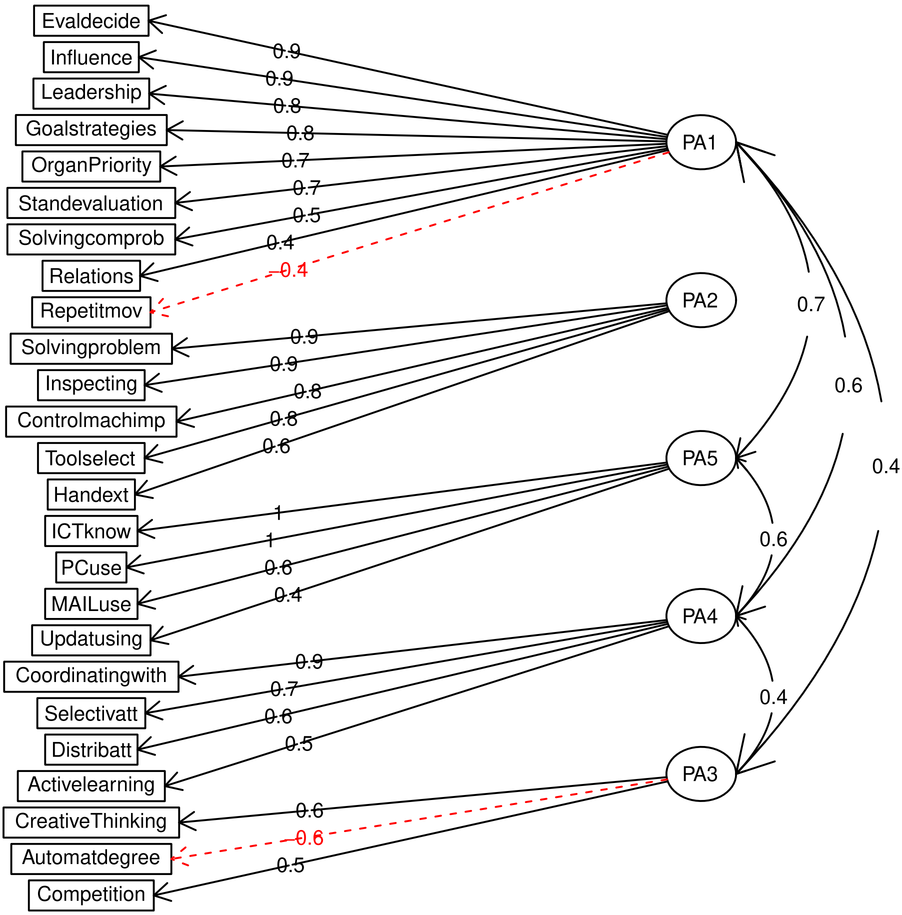

Figure 7. Factor analysis.

use of machinery and equipment (controlling machines, automation degree, inspecting) and activities reflecting a certain manual ability and autonomy of judgment in the choice of work tools and in the resolution of unexpected problems that may arise in the performance of tasks. This factor presents comparability with the Routine Task Index proposed by Autor (2015), but departs from the simple consideration of routinization and comprises elements related to the theory of the human capacity index proposed by Pfeiffer and Suphan (2015) and Pfeiffer (2018), which, to repeat, focuses on the role played by experience and ability to face unpredictable events. These aspects are captured in our case by the positive loadings of variables such as “Tool selection” and “Solving problems.” Indeed, especially in the assembly line—considered as one of the workplace most susceptible to automation—it might be necessary to perform a constellation of nonroutine tasks in order to prevent incidents, developing a high sensitivity to unpredicted changes, “keeping track of the whole environment with peripheral vision” (Pfeiffer, 2016: 12).

The third factor, responsible for another 14% of variance, collects variables related to learning activities and ICT skills. In particular, the use of computer and the knowledge of ICT represent the two variables exhibiting the highest loadings. Additionally, learning variables such as the need of keeping up to date with technical changes and applying new knowledge load positively, whereas hand dexterity shows a negative load. We labeld this factor *ICT skills* in order to emphasize the relative importance of those variables revealing the presence of ICT skills and active learning processes.

The fourth factor positively loads on three variables characterized by processes requiring an intensive use of cognitive knowledge, therefore mainly belonging to the first dimension of Table 1. The variables are active learning, selective and distributed attention. The coexistence of two seemingly contrasting variables, such as the ability to be

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Table 3. Factor analysis results (pattern matrix)

Variables	Power	C&M	ICT Know	Team	Creative
Distribatt	0.17	−0.06	0.11	**0.61**	0
Selectivatt	−0.27	0.11	0.24	**0.71**	0.19
CreativeThinking	0.29	0	0.07	0.02	**0.65**
Updatusing	0.26	**0.15**	**0.43**	0.27	0.2
Activelearning	0.32	−0.07	0.18	**0.49**	0.09
PCuse	−0.06	−0.12	**0.95**	0.09	−0.08
ICTknow	−0.2	0.19	**0.99**	0.03	0.07
MAILuse	0.34	−0.22	**0.57**	−0.03	0.08
Evaldecide	**0.95**	0.19	0.03	−0.26	0.26
Goalstrategies	**0.81**	−0.07	−0.07	0.02	0.26
OrganPriority	**0.7**	0.01	−0.01	0.14	0.23
Leadership	**0.91**	−0.05	−0.23	0.28	0.08
Influence	**0.92**	0.16	−0.19	0.02	0.03
Solvingcomprob	**0.54**	0.09	0.19	0.33	0.02
Solvingproblem	0.16	**0.92**	0.25	−0.15	−0.08
Toolselect	0.07	**0.75**	0.08	0.17	0.31
Repetitmov	**−0.42**	**0.35**	−0.29	−0.02	−0.01
Automatdegree	−0.05	**0.43**	0.2	−0.12	**−0.57**
Handext	−0.29	**0.56**	**−0.44**	0.09	0.3
Controlmachimp	0.02	**0.8**	−0.11	−0.01	−0.34
Standevaluation	**0.68**	**0.3**	0.1	0.27	−0.27
Inspecting	0.11	**0.9**	−0.14	0.06	−0.14
Relations	**0.45**	−0.28	−0.02	0.2	0.31
Competition	0.48	0.08	0.01	−0.28	**0.54**
Coordinatingwith	0.22	−0.04	−0.17	**0.85**	−0.18
SS loadings	6.32	3.83	3.47	3.11	2.31
Proportion Var	0.25	0.15	0.14	0.12	0.09
Cumulative Var	0.25	0.41	0.54	0.67	0.76

Note: Principal axis factoring with Promax rotation method. Values in bold indicate the highest variable loadings for each factor.

focused on a single task on the one hand, and the ability to simultaneously perform several activities on the other hand, signals a required degree of versatility to quickly react to the surrounding environment. Additionally, the third variable presenting a high loading is related to processes of coordination with other workers. We labeled this factor, which contributes to explain an additional 12% of variance, *Team*, being team work an activity generically involving high degree of collaboration, responsiveness to external stimuli, multi-functionality but at the same time, concentration on specific tasks. Therefore, in line with Lorenz and Valeyre (2005), we find that forms of cooperation among workers tend to exhibit notable learning dynamics.[19]

Finally, the last factor, accounting for the remaining 9% of variance, is mainly characterized by three variables: the absence of automated processes, the presence of a certain degree of competition, and the need to think creatively and develop new ideas.[20] We labeled this factor *Creative* since it identifies tasks involving creativity, but also forms

19 The authors make explicit reference to a "lean" model. In our case, we do not have sufficient elements (i.e. the presence of job rotations mechanisms) to define as "lean" the factor.

20 The lower percentage of the variance explained by the last factor is unavoidable, considering the descending order according to which factors are displayed. However, the presence of two "marker variables"—Creative Thinking and Competition, largely loading in one factor only—can be considered as a "pure measure" of the factor (Tabachnick *et al.*, 2007). This justifies, according to us, the inclusion of the fifth factor in our model, together with the result of the parallel analysis.

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of competition among workers. These variables mainly belong to both learning and social dimensions, according to Table 1.

How does the ex-post factor analysis face vis-à-vis the ex-ante categorization presented in Table 1? Overall, we do observe that the latent factors tend to capture our categorization: the variables related to autonomy and control load in the first factor, those related to routinarity and automation load in the second factor, while those one related to ICT skills load in the third factor. A notable exception is our predefined domain *Knowledge and Learning* which spans its variables into three factors, namely *ICT skills*, *Team* and *Creative*.

3.6 From micro to macro: factors across occupational categories

In this section, we perform a micro-to-macro analysis to understand how the identified five factors at four-digit level *distribute* across occupational categories at one-digit level of aggregation. In this respect, we want to characterize which are the prevalent traits of the activities conducted by occupational categories and how they differ among themselves.

Figure 8 presents five box-and-whisker plots for each of the identified factors, going from the left-hand to the right-hand side, from the top to the bottom panel, according to the factor relative importance. The box-plots allow to identify the distribution of the median, interquartile ranges, maximum and minimum values, and outliers per each one-digit occupational category.

Power, the first factor in Figure 8a, presents a clear descending pattern across the eight categories, with legislators, entrepreneurs, and managers presenting a higher than 1 median value and a low degree of variability. At the opposite end of the spectrum, elementary occupations have a negative, lower than –1, median level of power, with the maximum recorded value still less than zero. Together with the top-occupational category, only two other categories present a positive median value for power, namely intellectual and scientific workers, and technicians and associate professionals. However, the median value is lower than 1, and presents a low-end variability in both cases, reaching negative values. A complementary view comes from Figure A2a which presents the kernel density distribution per each factor grouped by occupational categories. From the figure clearly emerges how power is strongly concentrated in the top professional category and unevenly distributed across the rest of occupations.[21]

The second factor, *Cognitive and manual dexterity* presented in Figure 8b, is clearly concentrated among crafts, agriculture and specialized workers, and plant and machine operators with a median value around 1. The rest of occupations presents negative values for this factor. However, the degree of variability is extremely high. Notably, the kernel density distributions of intellectual and scientific workers, technicians, and service and sales workers overlap, as shown in Figure A2b. The latter finding highlights that there are some degrees of commonality, probably in the cognitive activities performed across distinct occupations.

The third factor, *ICT skills* presented in Figure 8c, mainly characterizes the top-four one-digit occupations, with notably higher values for intellectual and scientific workers whose median value is around 1. Additionally, legislators, entrepreneurs, and managers, which are characterized by the highest level of power, require similar use of digital tools and need to update their own knowledge as compared to technicians and associate professionals, and to clerical support workers, as shown by the overlap of the kernel density distributions in Figure A2c. All the bottom-four occupations present negative median values, although with a notable heterogeneity, particularly for service and sales workers, and for craft, agriculture and specialized workers, with ample ranges of variation.

A similar pattern across occupations, although less evident, emerges also for the *Team* factor, again with a higher median value for intellectual and scientific workers, as presented in Figure 8d. This factor presents multi-modality for the distribution of elementary occupations and bi-modality for technicians and associate professionals (Figure A2d) indicating that the variables behind the factor present a strong degree of inter-occupational heterogeneity.

Finally, the last factor, *Creative*, mostly belongs to scientific workers. It is negative for many occupational categories, including clerical support workers and plant and machine operators (cf. Figure 8e). It presents a strong degree of variability for sale and service workers, technicians and associate professionals, and crafts and artisans, whose distributions tend to overlap (cf. Figure A2e). In particular, the support of the distribution of crafts, agriculture and

21 Fligner-Policello tests have been run to assess the equality of pairwise distributions per each factor. The test confirms our interpretation of the results, whenever we detect difference or alternatively equality in the distributions.

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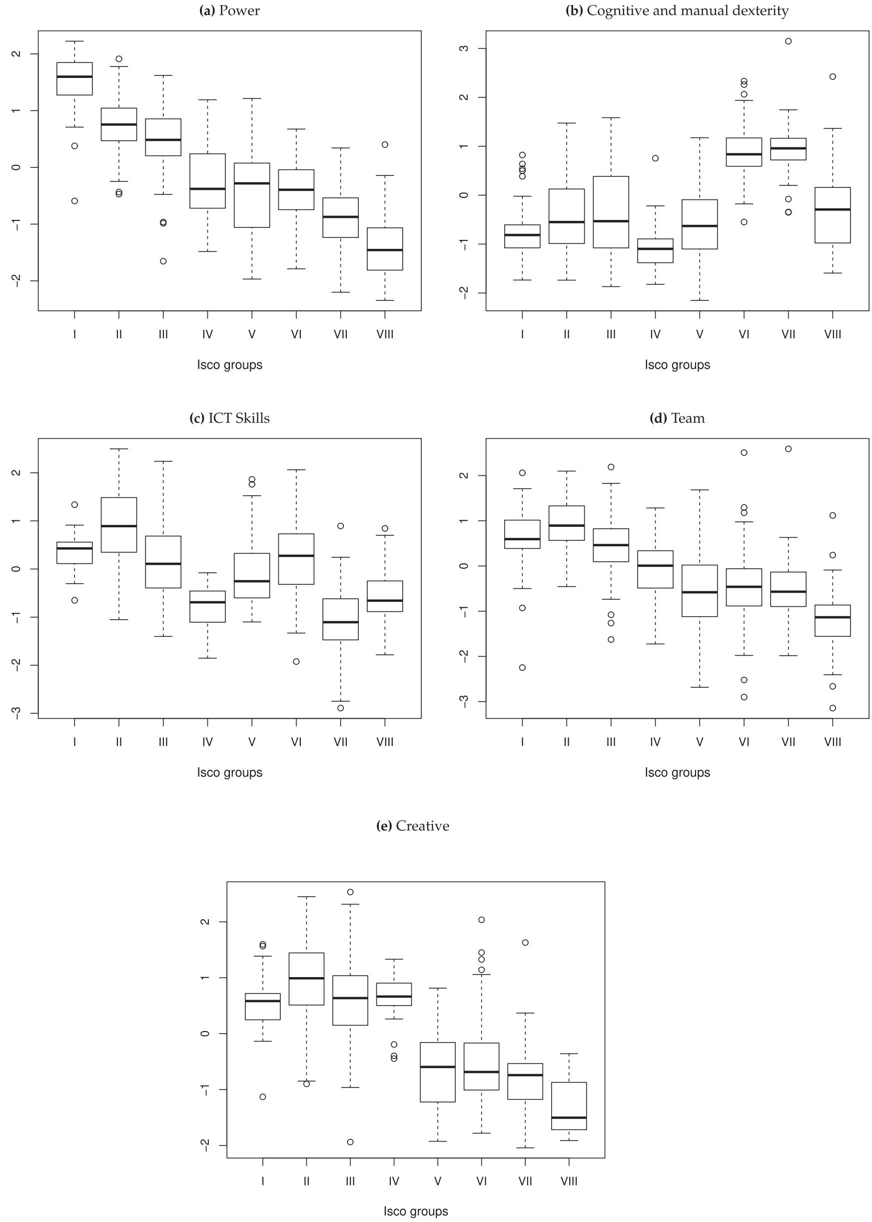

Figure 8. Box-and-whisker plots. (a) Power, (b) Cognitive and manual dexterity, (c) ICT Skills, (d) Team, and (e) Creative.

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specialized workers varies from negative to positive values probably because of the presence of highly specialized and creative craftsmen within this group.

In the following Table 4, we present the top-10 and bottom-10 occupations at four-digit level of disaggregation for each factor in order to provide a further validation of our analysis. Notably, the *Power* factor shows cases in which top- and bottom-occupations in the same sector of activity are in a respective opposite ranking: this is the case for nonqualified staff in catering services which ranks second in the bottom-tier, while entrepreneurs and directors of large companies in accommodation and catering services rank fifth in the top-tier. This confirms that the factor is

Table 4. Top and bottom 10 occupations (4-digit) by factor

Four-digit code	Loads	Description
Bottom-10 occupations—Power		
8421	−2.34	Manual workers and unqualified personnel in civil construction and similar professions
8142	−2.33	Nonqualified staff in catering services
8152	−2.27	Porters and similar professions
7232	−2.20	Conductors of machinery for the manufacture of other rubber products
8131	−2.11	Freight forwarders and similar workers
8221	−2.10	Domestic workers and related professions
7424	−2.03	Animal-drawn vehicle drivers
7422	−1.97	Bus, tram, and trolley drivers
5441	−1.96	Company staff and qualified family service staff
8151	−1.95	Bidding and related professions
Top-10 occupations—Power		
1124	2.22	General managers, departmental managers, and equivalent directors of state administrations, noneconomic public bodies, local authorities, universities, research institutions, and health
1121	2.22	Ambassadors, plenipotentiary ministers, and senior executives of the diplomatic career
1122	2.12	Government commissioners, prefects, and deputy prefects, heads and deputy heads of state police, questors, secretaries-general and related professions
1212	2.11	Entrepreneurs and administrators of large companies involved in mineral extraction, manufacturing, production, and distribution of electricity, gas, water, and waste management activities
1215	2.11	Entrepreneurs and directors of large companies in accommodation and catering services
1239	2.09	Other departmental directors and managers not elsewhere classified
1228	2.08	Directors and general managers of companies providing services to businesses and individuals
1227	2.04	Directors and general managers of banks, insurance companies, real estate agencies, and financial intermediaries
1123	1.93	Directors of the local school offices, superintendents of the national cultural heritage and equivalent
2217	1.91	Industrial and management engineers
Bottom-10 occupations—Cognitive and manual dexterity		
5131	−2.15	Models and similar professions
3347	−1.86	Agents and representatives of artists and athletes
4321	−1.82	Accountants
5125	−1.74	Home-based sellers, remote and similar professions
2523	−1.73	Notaries
1112	−1.73	Members of governing bodies and assemblies with legislative and regulatory power at the regional level and of autonomous provinces
1131	−1.66	Executives of the ordinary judiciary (Courts, Tribunals, Courts of Appeal, Court of Cassation)
4223	−1.62	Operators
8121	−1.59	Bailiffs and related professions
3322	−1.56	Banking technicians
Top-10 occupations—Cognitive and manual dexterity		
7161	3.14	Conductors of steam boilers and heat engines in industrial plants
8323	2.42	Unqualified personnel involved in fishing and hunting
6232	2.33	Engineers and repairers of aircraft engines
6216	2.26	Divers
6238	2.06	Naval mechanics and toolmakers
6451	1.93	Aquaculture and related professions
6453	1.92	Deep-sea fishermen
6215	1.87	Equipment and assemblers of metal cables for industrial and transport use

(continued)

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Table 4. Continued

Four-digit code	Loads	Description
6217	1.85	Specialists in electrical welding and ASME standards
6551	1.81	Stage machinists and toolmakers
Bottom-10 occupations—ICT skills		
7424	−2.04	Animal-drawn vehicle drivers
3427	−1.93	Athletes
5441	−1.92	Company staff and qualified family service staff
8142	−1.91	Nonqualified staff in catering services
5487	−1.91	Lifeguards and similar professions
8421	−1.86	Manpower and unskilled personnel in civil construction and related occupations
8221	−1.84	Domestic workers and related professions
8141	−1.82	Unqualified cleaning personnel in accommodation services and ships
8152	−1.79	Carriers and related professions
7443	−1.79	Conductors of cranes and lifting equipment
Top-10 occupations—ICT skills		
3123	2.53	Web technicians
2114	2.44	Analysts and software designers
2214	2.32	Electronic and telecommunications engineers
3125	2.31	Manager-technicians of networks and telematic systems
2213	2.30	Electrical engineers
2115	2.24	System designers and administrators
3122	2.13	Technical experts in applications
3124	2.05	Technical database managers
2623	2.03	Researchers and technicians with degrees in engineering and architecture sciences
6246	2.03	Installers, maintainers, and repairers of computer equipment
Bottom-10 occupations—Team		
8112	−3.14	Walking service providers
6516	−2.89	Tobacco leaf preparation and processing workers
5122	−2.68	Retail sale clerks
8111	−2.66	Street vendors of goods
6422	−2.51	Sheep and goat breeders and specialized workers
8322	−2.40	Unqualified staff for the caring of animals
5488	−2.32	Garage operators
8144	−2.31	Vehicle washers
1314	−2.24	Entrepreneurs and managers of small businesses in commerce
7265	−1.98	Workers in textile printing machinery
Top-10 occupations—Team		
7161	2.58	Conductors of steam boilers and heat engines in industrial plants
6232	2.50	Engineers and repairers of aircraft engines
3162	2.18	Pilots of aircraft
2418	2.09	Anesthetists
1121	2.06	Ambassadors, plenipotentiary ministers, and senior executives of the diplomatic career
2612	1.97	University lecturers in life and health sciences
2652	1.87	School inspectors and related professions
3133	1.82	Electrotechnics
2622	1.79	Researchers and technicians with a degree in life and health sciences
2413	1.78	Specialists in surgical therapies

(continued)

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Table 4. Continued

Four-digit code	Loads	Description
Bottom-10 occupations—Creative		
7264	−2.89	Workers involved in machinery for the processing of industrial yarns and fabrics
7265	−2.74	Workers involved in machinery for printing fabrics
7134	−2.35	Conductors of ovens and other plants for the production of bricks, tiles, and similar
7325	−2.21	Machine operators for the production and refining of sugar
7213	−2.14	Machine operators for the production of abrasives and mineral abrasive products
7143	−2.06	Papermaking plant operators
7182	−2.06	Conductors of furnaces and similar installations for the heat treatment of minerals
7313	−1.99	Workers in the refrigeration, hygienic treatment, and first-stage processing of milk
6516	−1.92	Tobacco leaf preparation and processing workers
7233	−1.86	Machinery operators for the manufacture of plastic and related products
Top-10 occupations—Creative		
2555	2.49	Artists of the popular culture and acrobats
2631	2.35	Professors from academies, conservatories and similar educational institutions
2554	2.31	Composers, musicians, and singers
3423	2.23	Instructors of techniques in arts
3171	2.09	Photographers and related professions
6324	2.06	Painters and decorators on glass and ceramics
2551	2.01	Painters, sculptors, designers, and restorers of cultural heritage
6332	1.95	Craftsmen of the artistic work of textiles, leather, and the like by hand
2552	1.93	Directors, art directors, actors, screenwriters, and set designers
2614	1.89	University lecturers in ancient, philological-literary, and historical-artistic sciences

actually able to uncover the hierarchical structure of the sector of activity. By inspecting the other factors, the selected occupations look to appropriately validate the analysis.

To sum up, we identified that the first factor in explaining four-digit level occupational variation is also the most concentrated at one-digit level of aggregation. Additionally, when comparing the distribution of the *Power* factor vis-à-vis the *ICT skills*, *Creative*, and *Team* factors, our proxies of learning processes, we do find a discrepancy between managing power and being endowed by knowledge, with, on the one hand, occupational categories, such as intellectual and scientific workers, and technicians and professionals, exerting less power than managers and legislators, and on the other hand, the latter being characterized by a significant lower degree of knowledge but also of creativity, according to the distribution of our fifth factor. Therefore, contrary to learning models typical of Northern economies (Lorenz and Valeyre, 2005: 430), which are characterized by the coexistence of a high degree of autonomy, strong learning dynamics and horizontal constraints—even for managers, professionals, and technicians—we find that autonomy and control tend to diverge with respect to learning processes in the Italian economy.

Overall, we dissect few activities, which map into occupational categories, requiring cognitive and manual dexterity as dominant traits, with generically negative median values, except for crafts and machine operators. Notably, the other occupational category which should be characterized by the predominance of this factor according to the RBTC classification, namely clerical support workers performing routinized cognitive activities, does not present a positive median value.

The level of team-working and practices of active learning are generically positive (but with low median values) only for the top-three categories of occupations, while remarkably the factor *Creative* presents top-end variability in occupations usually conceived to characterize low-skill workers, such as sale and service operators, and crafts and artisans. The latter might signal both the existence of creative practices or alternatively of high degree of competition among workers in the low-tier of occupations. Notably, all the three factors capturing attributes of learning processes and knowledge accumulation are more widespread across one-digit occupations with respect to the *Power* factor.

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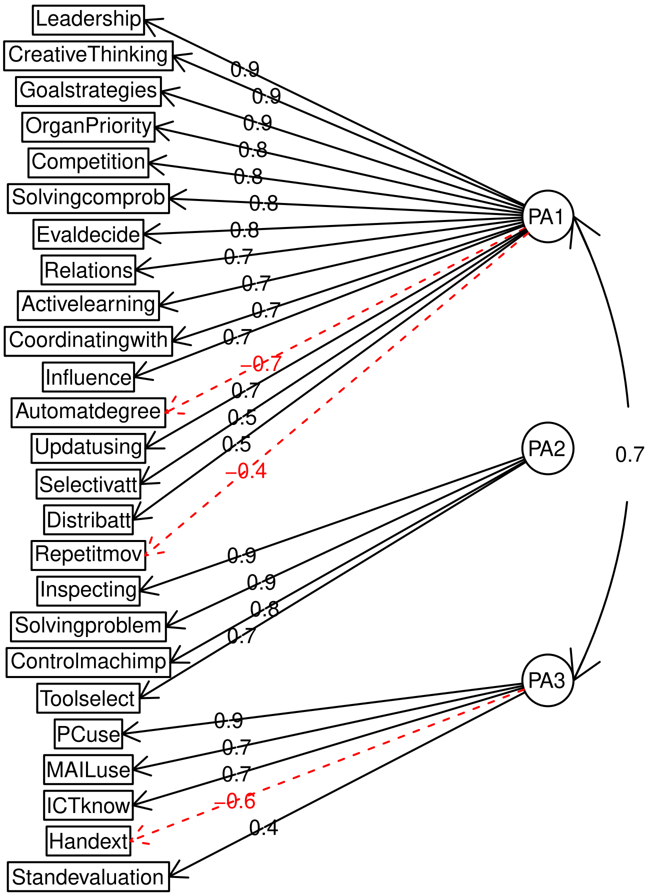

Figure 9. Factor analysis for employees.

4. Employed and self-employed workers

In this section, we intend to detect the extent to which our results might be affected by the forms of employment status behind occupations. Given that the primary factor in explaining cross-occupational variance derives from variables linked to autonomy in decision-making, in planning and in doing the job, one may suspect that the strong importance of the *Power* factor stems from self-employed workers, whose share is remarkably high in Italy. For this reason, we split the overall sample in two sub-samples, namely autonomous and dependent workers. This information derives from the ICP dataset where it is specified whether each five-digit worker has an autonomous or an employee status. Given that our unit of analysis is at four-digit level, we need to resort to an attribution criterion for each four-digit level occupational category. We opted for a routine according to which if more than 60% of the five-digit level occupations are autonomous, the corresponding four-digit level will be autonomous as well. The same procedure applies to employee workers. Using this cut-off, we are not able to attribute a status to only 74 occupations out of 507, therefore retaining the majority of them.[22]

Figures 9 and 10 present the results of the factor analysis for the two sub-groups. Figure 9 shows that only three out of five factors are now retained as significant for employees. However, the order remains unaltered, with the *Power* factor explaining most of the variation (41%), followed by *Cognitive and manual dexterity* and *ICT skills*, that respectively explain 15% and 17% of the variance. Clearly, by clustering into three components some variables

22 Alternative thresholds have been employed (80:20; 75:25; 70:30). However too many observations are lost when using the alternative thresholds (229; 190; 161, respectively).

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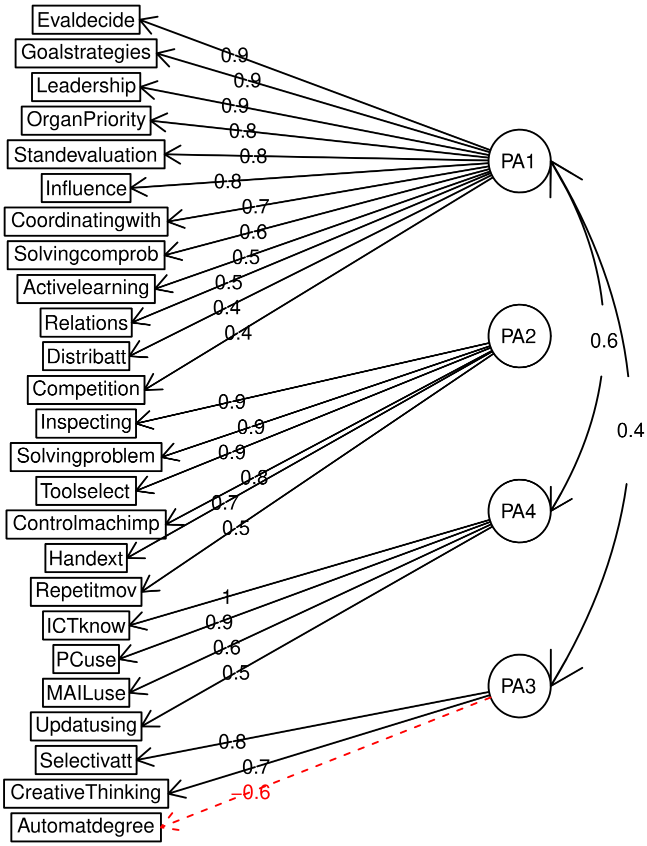

Figure 10. Factor analysis for self-employed workers.

before attributed to the *Creative* and *Team* factors now conflate into the first factor, which also loads learning variables. In case of self-employed workers, four out of five factors are retained, with *Power* explaining the highest percentage of variance (28%), *Cognitive and manual dexterity* explaining 17% of variance and *ICT skills* and *Team* explaining almost the same proportion of data variability (14% and 12% respectively). We therefore conclude that the emergence and relative importance of the *Power* factor is not driven by the employment status but it is instead an inherent trait characterizing the variability across occupations in the Italian economy. The same consideration applies to the remaining factors whose importance is relatively unaltered.

In the following, we compare the kernel density distributions of employees versus autonomous workers for the three common explaining factors, given the same occupational categories. We select some representative patterns which highlight both differences and similarities by factor-occupation. Figure 11a and b present the distributions of *Power* recovered by performing two independent factor analyses. By performing this exercise we are comparing two different populations of workers in terms of inherent characteristics of the working activities and in terms of size. However, we intend to understand how the factors behave according to the employment status, by macro-occupational categories. Take the case of legislators, entrepreneurs, and managers. Autonomous workers (purple distribution) present a much wider support in terms of *Power*, more concentrated on the right-hand side. When looking at technicians and professionals, the two populations present a largely overlapping support of the distributions, with a notably right long-tail, signaling stronger power attributes, for autonomous workers (cf. Figure 11b). In this respect, we do observe inter-occupational variability of the factor, according to the employment status.

Looking at the *Cognitive and manual dexterity* factor, comparing Figure 11c and d, we detect a more invariant behavior of the factor vis-à-vis the employment status: both machine and plant operators, and crafts, agriculture, and specialized workers, do not show strong differences in the support of the distributions when comparing employees

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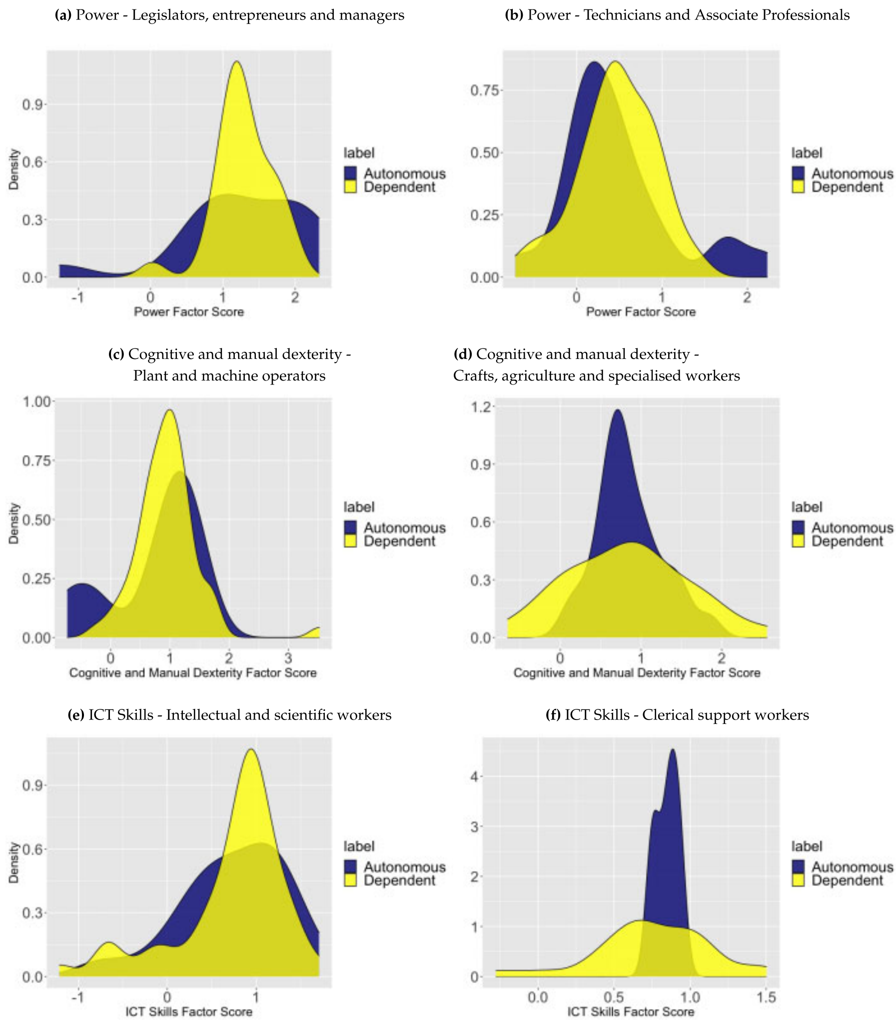

Figure 11. Kernel density distributions for employees and self-employed workers. (a) Power—Legislators, entrepreneurs and managers, (b) Power—Technicians and Associate Professionals, (c) Cognitive and manual dexterity—plant and machine operators, (d) Cognitive and manual dexterity—crafts, agriculture, and specialized workers, (e) ICT Skills—intellectual and scientific workers, and (f) ICT Skills—clerical support workers.

and autonomous workers. However, the modal behavior is significantly different when looking at crafts and specialized workers.

Finally, the *ICT skills* factor does not exhibit strong variability when comparing e.g. intellectual and scientific autonomous versus employed workers, but it does the opposite when looking at clerical support operators, whereby autonomous workers present a distribution concentrated on the upper support, while dependent workers exhibit a far wider heterogeneity.

In general, a word of caution is needed: in many respects, the population of self-employed workers is composed also by fictitious self-employed, who actually might durably contract even with a single buyer for repeated periods and are required to have their own VAT identification number, in order not to “weigh on” the firms for which they work. In this respect, the autonomous status might mask the effective status as dependent worker, leading to forms of dependent-self-employment (Williams and Lapeyre, 2017). Unfortunately, we do not have any reliable source to identify those forms of false positives, but there are clearly some one-digit level occupations, such as clerical support workers, which are by the inherent characteristics of the activities more “naturally” composed of employee workers

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although recorded as being self-employed. Related, we are not able to distinguish between incorporated self-employed workers, or formal business, and unincorporated self-employed ones, or informal firms (Levine and Rubinstein, 2017). However, the same status might embrace both high-paid professional workers (lawyers, engineers, architectures, physicians) and also low-paid ones (street vendors, door-to-door salesman).

5. Interpretations and conclusions

The goal of this paper has been to detect and describe the dominant traits of the Italian occupational structure, exploiting the vast and unique amount of information contained in the ICP database. In a context of vibrant economic and political debates on the effects of technological change on employment, a tall task consists in understanding what actually people do at work, avoiding to fall in simplifying classifications.

We accomplish that by means of a multistep empirical strategy. First, we build an ex-ante theoretical categorization of the dataset focusing on technological, organizational, and skill dimensions of the ICP questionnaire, covering three key areas of analysis namely, *knowledge and learning*; *work organization*, including *degrees of autonomy, routinariety, automation, control, and social interactions*; and finally *ICT skills*. We then move from this theoretical classification to the factor analysis performed on the selected variables to detect the presence of some hidden factors able to describe the almost 500 occupations at four-digit level of aggregation composing the dataset. Five latent factors allow to explain the variance among our variables, with the factor collecting attributes of *power* explaining most of the variability. Other relevant factors that do emerge allow to bundle important characteristics of work activities such as *cognitive and manual dexterity, ICT skills, creativity and team work*.

We find some rather striking results. First of all, occupational groups manifest strong heterogeneity in terms of the identified factors. This allows to conclude that the factor analysis pinpoints hidden components fueling this heterogeneity. Second, with reference to the factor-occupation link, we do find that:

- *Power* is strongly uneven distributed across one-digit occupational categories, concentrated among managers and legislators. Surprisingly, also categories expected to have a higher degree of power, such as producers of scientific knowledge, on average manifest a lack of it.
- Are those one making decisions more ICT skilled and exposed to active learning processes? Hardly so, in fact our *ICT skills* factor, collecting both learning activities and ICT skills, is similarly concentrated among e.g., clerical support workers and managers and legislators.
- *Knowledge* appears to be the most multifaceted trait to define occupations. In fact, its attributes are widely distributed both *among factors*, taking the forms of ICT skills updating, cognitive and manual dexterity and active learning, and *across occupations*, with clerical support workers and professionals presenting overlapping patterns, and with manual workers exercising their cognitive abilities to control machines or inspect equipments. This means that purported routinized activities are instead also characterized by the resolution of more or less complex problems. Indeed, knowledge attributes being the most scattered among both factors and occupations are also more pervasive. This signals the weakness of the "routine vs nonroutine" dichotomy to define activities and occupations.
- The degree of collaboration and team work appears to be rather weak, both in service and manufacturing-oriented occupational categories. The low degree of team-work activities clearly reflects the prevalence of autonomous jobs and small enterprises, which undermine the possibility of collaborations.
- Being creative is a privilege for scientists and intellectual workers and, to a lesser extent, for specialized crafts and artisans. Note, however, that power, autonomy, and creativity do not go hand in hand.

More specifically, the empirical evidence according to which the first one-digit occupational group—legislators, entrepreneurs, managers—displays the highest *Power* factor score does reflect two complementary results. On the one hand, this correctly points at occupations that hold decision-making roles, consistently with the structure of the ISCO classification. On the other hand, it does reflect the existence of usually neglected dimensions of control enhancement and hierarchical structure within organizations, which do not derive from the division of tasks among workers accordingly to their skills, but rather from the evolution of productive organizations shaped by social dynamics. If through the technical and bureaucratic organization of work "power was made invisible" (Edwards,

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1980: 110), one of the contribution of this paper consists in disclosing the importance of this component to study the occupational structure.

Moreover, our analysis offers a different perspective on occupations usually labeled as routinized by their degree of repetitiveness and related risk of substitution. Indeed, the second factor *Cognitive and manual dexterity* shows that a hidden level of complexity emerges in terms of continuous resolution of problems and dynamic selection of tools, even in standardized workplaces. This finding is in line with Pfeiffer (2018) which cautiously warns against the adoption of a strict definition of routine—nonroutine activities.

In addition, the Italian occupational structure reveals to be fragile in terms of ICT skills. These skills are concentrated in a restricted set of occupations and under-diffused among occupations characterized by a high degree of responsibility and power. This outcome confirms recent analyses pointing at the scarce level of digital literacy of the Italian population, which ranks 26th out of 28 EU countries in the human capital dimension defined by the Digital Economy and Society Index (EU, 2019). Moreover, the generalized low degree of the factor across occupations might be attributable to the "dwarfism" of firms (Fabiani *et al.*, 2005).

Italian occupations are also weak in terms of collaborative and worker involvement practices. At this stage, we do not have sufficient elements to completely characterize the entire set of HPWPs (job-rotation schemes, rewarding systems, internal labor markets). Nonetheless, this result is informative about the absence of managerial strategies promoting workers participation in the production process. Indeed, the adoption of lean practices also depends on managers' cultural and political visions of the production system (Vidal, 2013). In this respect, the Italian economy looks to be characterized by a relatively higher diffusion of individual-based and Tayloristic forms of work organization with respect to Northern European countries (Lorenz and Valeyre, 2005).

Our results clearly present some limitations, the two most relevant being the nature of knowledge we are able to capture, on the one hand, and the subjectivity in the replies to the questionnaire, on the other. With respect to the former, knowledge inside organizations has a complex structure: there exists knowledge on how to make things, let us call it *procedural knowledge*, but also—equally important—on how to design processes, to organize operations, to manage external relations (suppliers, clients, financing entities), let us call it *coordinative and relational knowledge*, the latter clearly overlapping with some attributes of power, and unevenly scattered across internal layers of the organization. Indeed, our analysis is mainly catching the first type of knowledge and only to a limited extent the second type, and this might limit the scope of our conclusions. Regarding the second limitation, given the subjective evaluations upon which the questionnaire is based, biases reflecting authority relations and conflict might inherently affect our results. To overcome such limitations, we call first for the replication of similar analyses comparatively across countries and second for the matching with employer–employee datasets in order to couple the more subjective nature of the occupational structure with the more objective patterns of firms organization.

To conclude, our analysis allows to pinpoint the role exerted by hierarchical structures, decision-making autonomy, and knowledge as the most relevant attributes characterizing the division of labor. In so doing, we expand beyond the atomistic discourse of being skilled-unskilled, or doing routine-nonroutine activities, appropriately considering the role of organizations and hierarchical layers. Prospective lines of research include the dynamic analysis of the ICP database, the study of the occupational determinants of income inequalities, the impact of technical change and trade upon work organization.

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Appendix

Further descriptive statistics and results

Table A1. ISCO classification by eight macro-groups

ISCO groups
I. Legislators, entrepreneurs and anagers
II. Intellectual and scientific workers
III. Technicians and associate professionals
IV. Clerical support workers
V. Service and sale workers
VI. Crafts, agriculture and specialized workers
VII. Plant and machine operators and assemblers
VIII. Elementary occupations

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Table A2. List of the selected variables

Variable	Question	1st step	2nd step	3rd step
ProOthers	Those who carry out this work perform tasks that commit them to work also for the benefit of others	Yes	Yes	No
SupervisorSupport	Those who do this work can count on the support of their supervisors	Yes	Yes	No
SupervisorTrain	Those who do this work can count on supervisors who provide good training for staff	Yes	Yes	No
ExperIdeas	Those who do this work can experiment with their own ideas	Yes	No	No
AutoPlanning	Those who do this work plan their activities with little supervision	Yes	Yes	No
AutoDecisions	Those who do this work can make their own decisions	Yes	Yes	No
Leadership	The work requires the willingness to guide people, to take charge and to give opinions and directives	Yes	Yes	Yes
Adaptability	The job needs to be open to both positive and negative changes, as well as to strong variability in the workplace	Yes	Yes	No
DetailsAttention	The work requires attention to detail and to be thorough in completing the tasks	Yes	Yes	No
Independence	The work requires that you head without or with minimal supervision and depend solely on yourself to complete the work	Yes	Yes	No
Innovation	The work requires creativity and alternative ways of thinking to produce new ideas and answers to work problems	Yes	Yes	No
AnalyticThought	The work requires analyzing information and using logic to address issues and problems	Yes	Yes	No
ProcessControl	Check and review information from materials, events, or the environment to identify or evaluate problems	Yes	Yes	No
Inspecting	Inspect equipment, structures, or materials for causes of error, or other problems or defects	Yes	Yes	Yes
QualityEvaluation	Estimate the value, the importance, or the quality of things or people	Yes	Yes	No
StandardsEvaluation	Use relevant information and individual opinions to determine whether events or processes comply with standards, laws, or regulations	Yes	Yes	Yes
DecisionTaking	Analyze information and evaluate results to choose the best solution and to solve problems	Yes	Yes	No
CreativeThinking	Develop, design, or create new applications, ideas, relationships, and new systems and products (including artistic contributions)	Yes	Yes	Yes
GoalStrategies	Establish long-term objectives and specify strategies and actions to achieve them	Yes	Yes	Yes
PlanningWork	Schedule events, plans, and activities or the work of other people	Yes	Yes	No
ManagMachine	Use both control mechanisms and direct physical activity to operate machines or processes (excluding computers and vehicles)	Yes	Yes	No
PcUse	Use computers and computer systems (software and hardware) to program, write software, adjust functions, enter data, or process information	Yes	Yes	Yes
Communicate	Provide information to superiors, colleagues, and subordinates, by phone, in writing, by e-mail or personally	Yes	Yes	No
Relations	Create constructive and cooperative working relationships and maintain them over time	Yes	Yes	Yes
CoordinatOther	Ensure that the members of a group work together to accomplish the assigned tasks	Yes	Yes	No
ActivateTW	Encouraging and increasing mutual trust, respect and cooperation between members of a group	Yes	Yes	No
GuidingOthers	Guiding and directing subordinates by setting standards in performance and control of performance	Yes	Yes	No
TrainingOthers	Identify the growth needs of other people and train, mentor, or help other people improve their knowledge and skills	Yes	Yes	No

(continued)

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Table A2. Continued

Variable	Question	1st step	2nd step	3rd step
MailUse	How often does your profession require the use of e-mail?	Yes	Yes	Yes
FaceToface	How many contacts with other people (by phone, face-to-face, or otherwise) are you required to have in the course of your work?	Yes	No	No
TeamWorkImportance	How important is it in the performance of your work to interact personally with colleagues at work or to be part of teams or working groups?	Yes	Yes	No
GuidingOthersImp	How important is it in carrying out your work to coordinate or guide others in carrying out work-related activities?	Yes	Yes	No
ProductResp	How much responsibility do you have for the production and performance of other workers in the course of your work?	Yes	Yes	No
RipetitiveMovements	How long does it perform repetitive movements in your work?	Yes	Yes	Yes
FreeDecision	How free are you in your job to make unsupervised decisions?	Yes	No	No
AutomationDegree	How automated is your work? (linked to automatic processes)	Yes	Yes	Yes
Precision	How important is it in your work to be very precise or accurate?	Yes	Yes	No
RipetitivActivities	How important are repetitive physical or mental activities in your work over a relatively short period of time (less than 1 h)?	Yes	Yes	No
FreeGoalTasks	How free are you to define the tasks, priorities and objectives of your work?	Yes	Yes	No
Competition	How competitive is your work? (requires constant comparison with the performance of colleagues/other workers)	Yes	Yes	Yes
RigiDeadlines	How often does your work require deadlines that cannot be postponed?	Yes	Yes	No
MachineControlImport	How important is it in your work to keep sequences of machinery and equipment under control?	Yes	Yes	Yes
RegularOrganization	How regular is the organization of your work?	Yes	Yes	No
WeeksHours	How many hours do you work in a typical week?	Yes	No	No
HandsDexterity	Ability to quickly move hand, hand and arm together or both hands to grab, manipulate, or assemble objects	Yes	Yes	Yes
Tenure	How many years have you been in this profession?	Yes	No	No
Coordinate	Do you have the task of coordinating the work done by other people?	Yes	No	No
Update	How do you generally carry out the updating required by your profession?			
	It is promoted by the company for specific work needs	Yes	No	No
	It is promoted by the company through systematic updating programs	Yes	No	No
	It's entrusted to the personal initiative	Yes	No	No
UpdateFrequency	How often does the update take place?			
	Occasionally	Yes	No	No
	Once a year	Yes	No	No
	Several times a year	Yes	No	No
	It is a continuous activity	Yes	No	No
Updatuse	Keep up to date with technical changes and apply new knowledge	Yes	Yes	Yes
EntryTraining	If someone were hired (...), would they be required to follow a professional training course organized by the company?	Yes	No	No
CollegueTraining	If someone were hired (...), would they be required to work alongside colleague?	Yes	No	No
Innovation	In the last 3 years, have external factors intervened and changed the way in which your profession is carried out?			
	New/other technologies or machines introduced	Yes	No	No
	New/other products or services produced	Yes	No	No
	New/other materials used	Yes	No	No
	New/other work organization or organization of the undertaking or body	Yes	No	No
	New/other regulatory references	Yes	No	No
ItalKnowledge	Knowledge of the Italian language	Yes	No	No
ForeignKnowledge	Knowledge of a foreign language	Yes	No	No
CriticalThinking		Yes	Yes	No

(continued)

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Table A2. Continued

Variable	Question	1st step	2nd step	3rd step
	Use logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions, or approaches to problems			
ActiveLearning	Understand the implications of new information for the solution of present and future problems and for decision-making processes	Yes	Yes	Yes
Monitor	Monitor and evaluate the work performance of individuals, other people or organizations to improve or correct it	Yes	Yes	No
CoordinatWith	Coordinate their actions with those of others	Yes	Yes	Yes
SolvingComplProblems	Identify complex problems and collect information to evaluate possible options and find solutions	Yes	Yes	Yes
OperativeAnalysis	Analyze the characteristics and requirements of tools, services, or products needed to implement a project	Yes	Yes	No
ToolSelect	Identify the tools needed to do a job	Yes	Yes	Yes
Programming	Writing computer programs for various purposes	Yes	Yes	No
QualityControl	Conduct tests and inspections of products, services, or processes to assess their quality or performance	Yes	Yes	No
MachineSurveillance	Check level measurements, dials, or other indicators to ensure that a machine is working properly	Yes	Yes	No
OperationsControl	Control the operation and activity of equipment and systems	Yes	Yes	No
SolvingProblems	Determine the causes of operating errors and decide what to do to solve them	Yes	Yes	Yes
SystemAnalysis	Determine how a "system" should work and how environmental, operational, or situational changes can affect its results	Yes	Yes	No
EvaluateSystem	Identify measures or indicators of the performance of a system and the actions needed to improve or correct them (. . .)	Yes	Yes	No
EvaluateDecide	Evaluate the costs and benefits of possible actions to choose the most appropriate	Yes	Yes	Yes
ManageTime	Manage your own time and that of others	Yes	Yes	No
IdeasProduction	Ability to present a large number of ideas on a subject (the number of ideas is important, not quality, fairness, or creativity)	Yes	Yes	No
Originality	Ability to produce unusual and witty ideas on given issues or situations or to find creative solutions to solve a problem	Yes	Yes	No
SelectiveAttention	Ability to focus on a task for a long time without distraction	Yes	Yes	Yes
DistributedAttention	Ability to follow two or more different activities or sources of information at the same time	Yes	Yes	Yes
Busy	Those who do this work are constantly engaged in	Yes	Yes	No
TasksAlone	Those who do this work perform their tasks alone	Yes	Yes	No
DifferentActivities	Those who do this work are busy every day in different activities	Yes	Yes	No
Upgrading	Those who do this work have the opportunity to make career advances	Yes	Yes	No
DirIstrucOthers	Those who do this work give guidance and instructions to others	Yes	Yes	No
Influence	How often do your decisions affect other people or your employer's image or reputation or financial resources in your work	Yes	Yes	Yes
ICTKnow	Computer science and electronic knowledge	Yes	Yes	Yes
OrgPriorities	Set specific objectives and plan the work defining priorities, organization, and timing of implementation	Yes	Yes	Yes

Yes and No indicate the steps in which the variables have been used or discarded.

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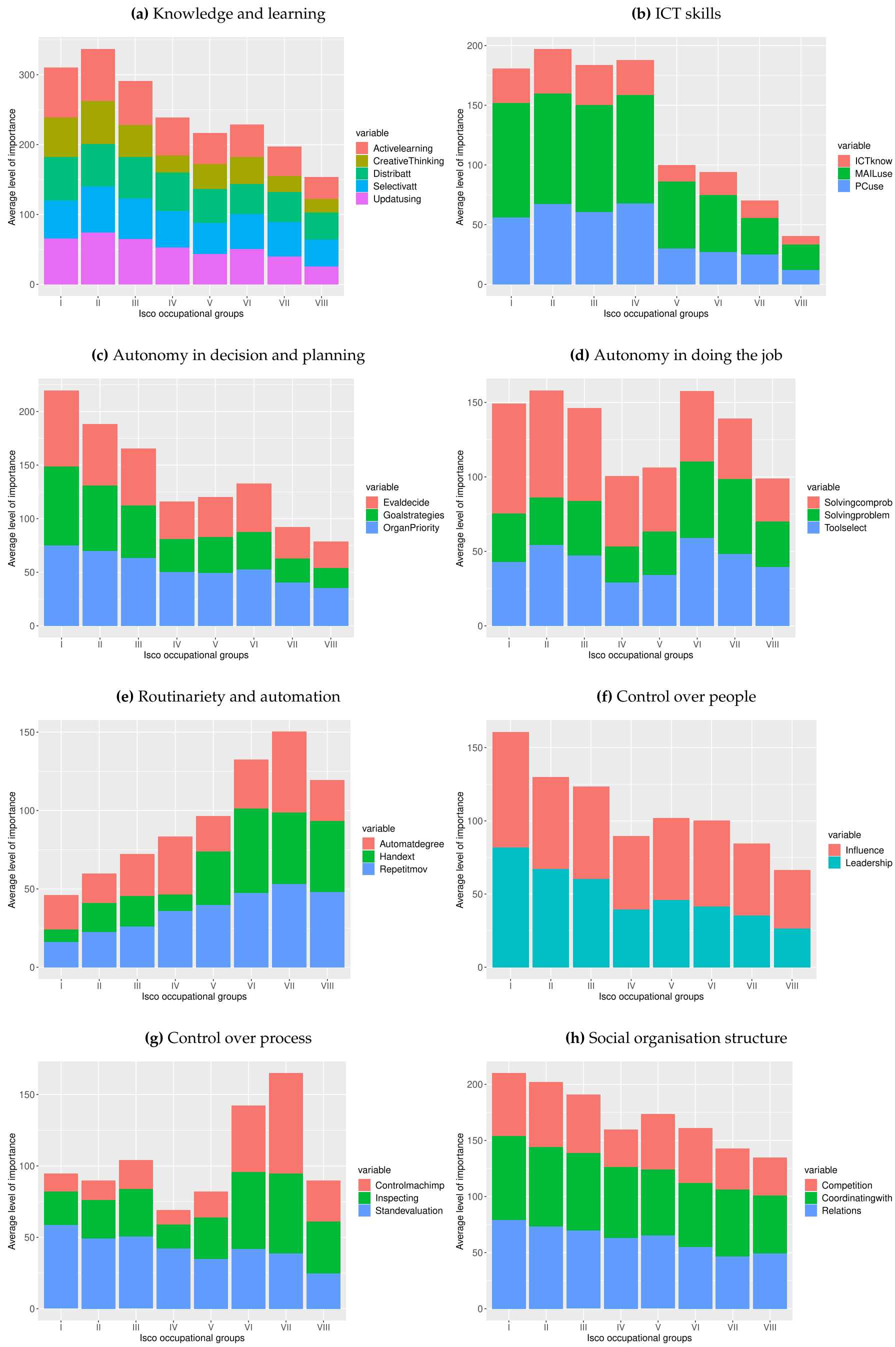

Figure A1. Domains—average values by ISCO groups. (a) Knowledge and learning, (b) ICT skills, (c) Autonomy in decision and planning, (d) Autonomy in doing the job, (e) Routinariety and automation, (f) Control over people, (g) Control over process, and (h) Social organization structure.

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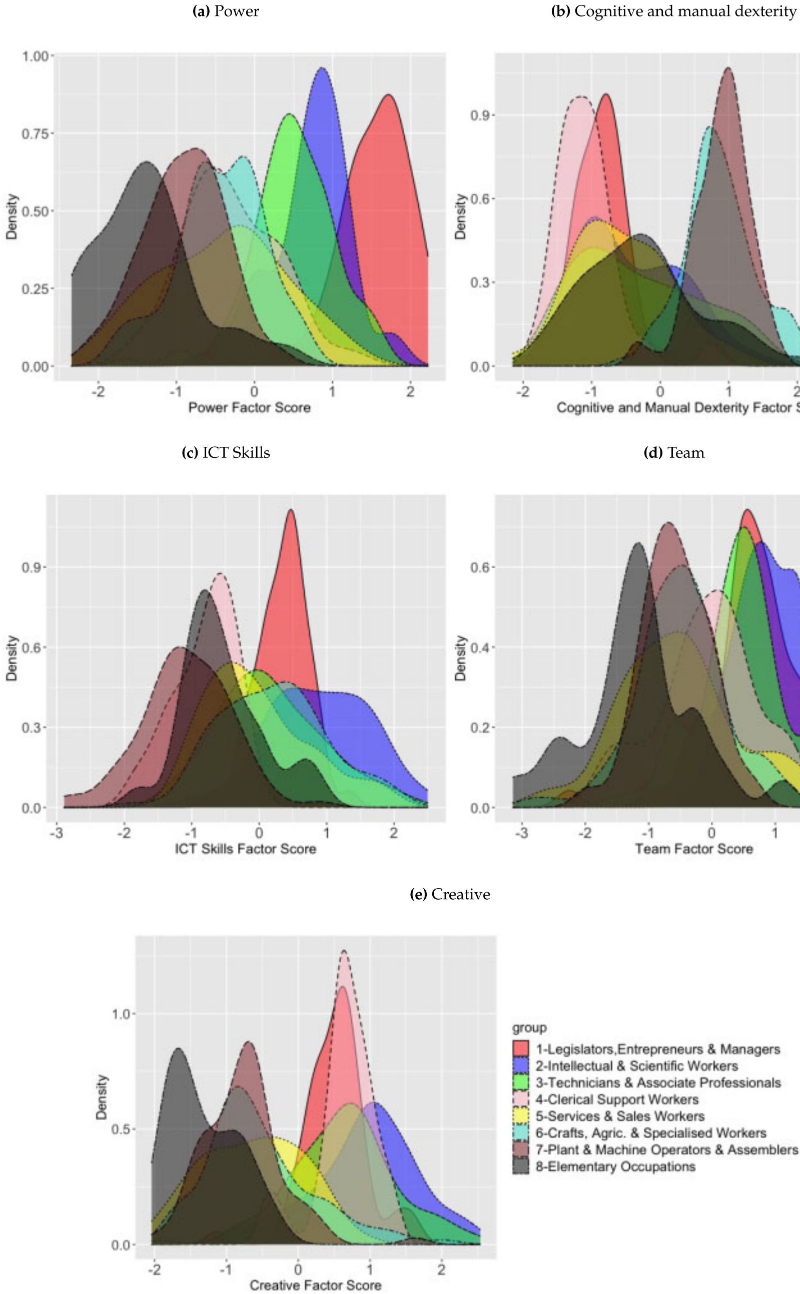

Figure A2. Kernel density distributions of the five factors by ISCO groups. (a) Power, (b) Cognitive and manual dexterity, (c) ICT Skills, (d) Team, and (e) Creative.

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